UNIVERSITY OF CALIFORNIA

Los Angeles

Optimization of Reservoir Operation and Rule Curves by Mixed-Integer Programming

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Civil Engineering

by

Ming-Yen Tu

2002

UMI Number: 3058521

UMI Microform 3058521

ProQuest Information and Learning Company
300 North Zeeb Road
P.O. Box 1346
Ann Arbor, MI 48106-1346

The dissertation of Ming-Yen Tu is approved.

Thomas C. Harmon

Keith D. Stolzenbach

Lieven Vandenberghe

William W-G. Yeh, Committee Chair

University of California, Los Angeles

2002

To my family

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGMENTS

I would like to gratefully thank my graduate advisor, Professor William W-G. Yeh. His extraordinary expertise on water resources planning and management has provided great guidance in completing this dissertation. In addition, his personal attributes of gentleness, thoughtfulness, and hard-work have had a dramatic effect on my life philosophy. I also would like to thank Professors Thomas C. Harmon, Keith D. Stolzenbach, and Lieven Vandenberghe for their willingness to serve as my dissertation committee and for their insightful suggestions and comments.

I am indebted to my study companion, Frank T-C. Tsai. In these four years, he has shown an unselfish willingness to help me in the preparation of my research. I also would like to thank my officemates: James McPhee, Li-Fang Chang, Jason Fisher, and Brent Thomas. Working with them has been a great experience. They have not only enhanced my engineering study, but also been helpful to my life in the United States. As an international student, writing a formal paper in English can be a daunting task; I acknowledge Joe Yoon for helping me to edit this dissertation.

I am extremely grateful to my wife, Tiffany Chiang. I thank her for her inspiration and encouragement to help me through this chaotic research journey. She was always beside me when I was lost in study. Because of her, I have also realized that life is full of much joy and happiness.

I would like to thank my parents, sisters and brother for supporting me even from thousands of miles away. To me, living and studying out of my country has been very challenging. One phone call from my family provided much encouragement and support.

The research reported in the dissertation is partially supported by the Water Resources Bureau, Ministry of Economic Affairs, Taiwan, R.O.C. and by the University of California Water Resources Center through project W-934.

VITA

August 21, 1972	Born, Kaohsiung, Taiwan
June, 1994	Bachelor of Science Department of Hydraulics and Ocean Engineering National Cheng Kung University Tainan, Taiwan
June, 1996	Master of Science Department of Civil Engineering National Taiwan University Taipei, Taiwan
July, 1996-June, 1998	Research Assistant Hydraulic Research Institute National Taiwan University Taipei, Taiwan
September, 1998-present	Graduate Student Researcher Department of Civil & Environmental Engineering University of California, Los Angeles Los Angeles, California

PUBLICATIONS AND PRESENTATIONS

Hsu, N.-S., Yeh, W. W-G., Yang, S., Louie, P. W. F., Tu, M.-Y., Wang, P.-W., and Fu, H.-Y. (1997). " A trend analysis of water supply-demand in Taiwan (II)." *Proj. Completion Rep. to Water Resource Bureau*, Taipei, Taiwan, R.O.C. (in Chinese)

Hsu, N.-S., Yeh, W. W-G., Yang, S., Tu, M.-Y., and Kuo, C.-K. (1998). " A trend analysis of water supply-demand in Taiwan (III)." *Proj. Completion Rep. to Water Resource Bureau*, Taipei, Taiwan, R.O.C. (in Chinese)

Hsu, N.-S., Yeh, W. W-G., Tu, M.-Y., Tsai, F. T-C., Wei, C.-C., and Hsieh, Y.-C. (2000). "Evaluation of reservoir management and operations in Taiwan." *Proj. Completion Rep. to Water Resource Bureau*, Taipei, Taiwan, R.O.C. (in Chinese)

Hsu, N.-S., Yeh, W. W-G., Tu, M.-Y., Chang, L.-F., and Wei, C.-C. (2001). "Risk analysis of reservoir operations with sediment removal." *Proj. Completion Rep. to Water Resource Bureau*, Taipei, Taiwan, R.O.C. (in Chinese)

Tu, M.-Y., Hsu, N.-S., and Yeh, W. W-G. (2002). "Optimization of reservoir management and operation with hedging rules." *J. Water Resour. Plng. and Mgmt.*, ASCE (in press).

Tu, M.-Y., Tsai, F. T-C., and Yeh, W. W-G. (2001). "Optimization of water distribution and water quality by genetic algorithm and nonlinear programming." Fall Annual Meeting, American Geophysical Union, December 10-14, 2001, San Francisco, CA.

Yeh, W. W-G., Yang, S., and Tu, M.-Y. (1999). "An analysis of long-term water supply-demand balance in Central Taiwan." *Proj. Completion Rep. to Water Resource Bureau*, Taipei, Taiwan, R.O.C. (in Chinese)

ABSTRACT OF THE DISSERTATION

Optimization of Reservoir Operation and Rule Curves

by Mixed-Integer Programming

by

Ming-Yen Tu

Doctor of Philosophy in Civil Engineering

University of California, Los Angeles, 2002

Professor William W-G. Yeh, Chair

Reservoir operation plays an important role in managing a regional water distribution system. During normal periods of operation, when inflows are plentiful, it is not difficult to distribute the available stored water from different reservoirs to meet the planned demands imposed by competing users. However, during periods of drought, or when anticipating a drought, the planned demands cannot be met completely, and a water shortage occurs. Therefore, a standard policy is needed to provide the rules for operating the reservoir to efficiently utilize the water. As a result, the rule curves and hedging rules are introduced as guidelines for the reservoir management and operation.

This study develops a mixed-integer linear programming (MILP) model that simultaneously considers both the rule curves and hedging rules to optimize the management and operation for a multi-purpose, multi-reservoir system. To minimize the impact of drought, the hedging rules effectively reduce the ongoing water supply to balance with the target storage requirement.

A mixed-integer nonlinear programming (MINLP) model is then developed based on the proposed MILP model to evaluate and modify the current rule curves and hedging rules. Due to the mathematical complexity of this MINLP model, a number of methodologies are proposed to solve this model. These methodologies are: Generalized Benders Decomposition, Penalty Coefficient Methods, Pseudo-integer Method, Simulated Annealing, and one mathematical transformation technique. The results of these methodologies are explored and investigated. After examining the performance of these methodologies, the transformation technique seems best suited to solving this proposed MINLP model.

A multi-reservoir system in the southern region of Taiwan is used as an actual case study to demonstrate the capability and utility of the proposed models. The results obtained indicate that the MILP model can efficiently utilize the water resources when incorporating the current rule curves and hedging rules. In addition, the new set of rule curves and hedging rules obtained by the MINLP model can successfully improve the performance of the current system operation.

CHAPTER 1 INTRODUCTION

In water resources planning and management, the general purpose of system operation for a regional water distribution system is to utilize water appropriately and efficiently. A regional water distribution system includes: rivers, streams, reservoirs, power plants, diversion structures, pumping stations, water users, channels and pipes. System operation must consider all the above components in order for the system to operate as efficiently as possible. Consequently, system managers need to take into account the system complexities involved to maximize efficiency. In general, the primary concern in system operation is water supply. Among system components, reservoir operation plays a significant role in fulfilling water supply.

Reservoirs are usually constructed for two purposes: water storage and water release. Unfortunately, these two purposes conflict with each other. The decision between these two competing purposes of either water storage or release can severely affect water usage for the entire system. If the current amount of water release is abundant, the water for future use may not be plentiful and have serious impact during periods of drought. If the current stored water is plentiful, the reservoir may not have enough space to store potential flood water and cause severe downstream damage. Therefore, system managers are responsible for determining a standard operating guideline to appropriately operate reservoirs.

A large-scale regional water supply system normally includes several single- or multi-purpose reservoirs. A single-purpose reservoir is designed for a single purpose such as municipal water supply. In contrast, a multi-purpose reservoir has multiple functions including: hydropower generation, flood control, navigation, fish and wildlife enhancement, and recreation. In addition, a multi-purpose reservoir functions to control agricultural, municipal and industrial water supply. The complexities of a multi-purpose, multi-reservoir system generally require release decisions made through the use of an assisting tool such as a simulation or optimization model.

In general, simulation models are able to capture the actual physical characteristics of a system. However, the process of obtaining the most beneficial operating policies involves the repeated implementation of simulation models through a trial and error process. In contrast, while optimization models may not consider all the complex details of a system (i.e. assumptions may be set beforehand), they are more efficient in providing optimal policies for decision making.

In recent years, optimization models have been used successfully to manage and operate complex reservoir systems. Yeh (1985), Simonovic (1992), Wurbs (1993), Wurbs (1996), ReVelle (1997), and Momoh et al. (1999a,b) have reviewed optimization model literature extensively and provide evaluations on various models. The choice of an appropriate optimization model depends on the following considerations: system characteristics, data availability, and the specified objectives and constraints.

1.1 Scope of Study

During normal periods of operation when inflow is plentiful, meeting reservoir operating goals and target storage does not pose a problem. However, during periods of drought or when anticipating a drought, it may not be possible to reach the storage target because of an inflow shortage. To minimize the impact of drought and consequent shortages in current and future water supply, reservoir rule curves are coupled with hedging rules to balance the shortage in water supply with the storage target.

This study is aimed at developing a multi-purpose and multi-resrvoir model to optimize the joint operation for a regional water supply system with regard to reservoir rule curves and hedging rules. This proposed optimization model can help plan for the operation of a multi-reservoir system during drought periods. Furthermore, this optimization model will also be expanded to evaluate and modify current rule curves and hedging rules for superior operation performance.

1.2 Objectives of Study

The objectives of this study are:

1. to develop a mixed-integer linear programming (MILP) model to optimize the joint operation of a multi-purpose and multi-reservoir system, incorporating rule curves and hedging rules;

2. to expand the above-mentioned MILP model to a mixed-integer nonlinear programming (MINLP) model to evaluate and modify the current rule curves and hedging rules; and
3. to apply the developed optimization models to a regional water distribution system in Southern Taiwan.

1.3 Dissertation Overview

The remaining content of this dissertation is outlined as follows. Chapter 2 includes a literature review concerning the optimization of regional water distribution systems. In addition, this chapter also discusses a number of past studies concerning reservoir operation in normal and dry situations. Chapter 3 describes the basic concept of developing an optimization model to deal with the operation of regional water distribution systems. The introduction of reservoir rule curves and hedging rules is then presented to provide the basic idea for operating reservoirs.

Chapter 4 presents a mixed-integer linear programming (MILP) model that is capable of optimizing the reservoir operation incorporating rule curves and hedging rules. The capability of this model is tested by a simplified system application. Chapter 5 proposes a mixed-integer nonlinear programming (MINLP) model, which is used to obtain a new set of rule curves and hedging rules to improve current system operation. Several methodologies are presented to solve this model and the results are compared and discussed. The model is then applied to a simplified system to test its capability.

Chapter 6 describes the application of the proposed MILP and MINLP models on a regional water distribution system - the southern regional water supply system in Taiwan. The model results are then examined and discussed. Finally, the conclusions and future work of this study are presented in Chapter 7. At the end of each chapter, corresponding tables and figures are included for the convenience of the reader.

CHAPTER 2 LITERATURE REVIEW

There are a lot of studies concerning the optimization of regional water distribution systems in literature. The following section will review a number of these studies. In addition, the subsequent section will also summarize several studies involving reservoir operation during normal and dry periods.

2.1 Optimization of Regional Water Distribution Systems

Optimization techniques have already proven their applicability and robustness to many subjects concerning regional water distribution systems. The application of optimization techniques have been demonstrated in the following areas: (1) optimal network design (Ostfeld and Shamir, 1996; Taher and Labadie, 1996; Varma et al., 1997; Xu and Goulter, 1999); (2) reliability analysis (Su et al., 1987; Guercio and Zuxin, 1997); (3) water network leakage analysis (Vairavamoorthy and Lumbers, 1998; Alonso et al., 2000; Bach et al., 2000).

The following studies focused on water supply in a regional water distribution system. Kuczera (1989) presented a network linear program formulation for determining water assignments in a multireservoir system over some time horizon. The computing efficiency of this formulation was demonstrated as superior to the conventional linear programming formulation. Hsu and Yeh (1992) developed a linear programming (LP)

procedure utilizing the Dantzig-Wolfe decomposition method to solve a facility planning problem for a water supply system. Diba et al. (1995) presented a planning model incorporating a directed graph algorithm and an LP procedure to assist the system operation for a large-scale water distribution system. This model demonstrated its applicability and versatility via a real water distribution system. Sun et al. (1995) reported an embedded generalized network flow model representing a water distribution problem and discovered a solution via a fast network algorithm. Yang et al. (1996a) proposed a mechanical reliability methodology using deterministic analysis to describe the probability of source-demand connectivity. Yang et al. (1996b) presented a performance reliability methodology using stochastic analysis to evaluate the supply level that a system can provide under random component failures.

Occasionally, water quality is considered simultaneously with water supply in order to optimize the operation of a regional water distribution system. Ostfeld and Shamir (1993a) reported a steady state, nonlinear operation model for a multiquality network. As opposed to other studies on directional graph, the undirectional pipes were incorporated in their methodology. The steady state optimization model was further extended by Ostfeld and Shamir (1993b) to incorporate the unsteady state solute transport in the water distribution system. Yang et al. (2000) presented preliminary research on the optimization of a regional water distribution system with blending requirements. In their study, a nonlinear multicommodity flow model was proposed to accommodate the blending requirements and perfect mixing conditions.

2.2 Reservoir Operation

In a regional water distribution system, the reservoir operation is an essential key in optimizing system practice. If inflow is plentiful, the reservoir operation is not a serious issue. However, this ideal situation may not happen in every water resource system. If the water is not plentiful, system planners and managers need to decide how to operate the reservoirs to reduce drought damage and utilize water more efficiently. Therefore, the development of a useful reservoir operation guideline is critical.

In many practical situations, operating rules (also referred to as operating policies) are established at the planning stage of the proposed reservoir. These rules then provide guidelines for reservoir releases to meet planned demands. The following literature review will report past studies on reservoir operation in normal and drought situations.

2.2.1 Normal Situation

Bhaskar and Whitlatch (1980) developed a backward dynamic program algorithm to obtain the optimal monthly releases for a single multi-purpose reservoir. Karamouz and Houck (1982) proposed an algorithm that consisted of a deterministic dynamic program, a regression analysis, and a simulation model to generate the annual and monthly operating rules for a single reservoir. Sand (1984) used stochastic dynamic programming to obtain optimal operating policies for the water supply of reservoirs in parallel. Using a genetic algorithm, Oliveira and Loucks (1997) derived optimal

operating policies for a multi-reservoir system. The above-mentioned studies have focused on reaching the reservoir release target as closely as possible.

2.2.2 Drought Situation

A small number of studies on hedging rules have been reported in literature. Shih and ReVelle (1994) developed a continuous linear hedging rule for a single water supply reservoir. They formulated a nonlinear mixed integer programming model that minimized the maximum deficit while considering a constant demand. After obtaining the optimal rule, they converted the continuous hedging rule into multiple discrete hedging rules which are more appropriate for practical applications. Shih and ReVelle (1995) developed a multiple hedging model using mixed integer programming for a single water supply reservoir. The primary purpose of the model was to maximize the number of months in which no water rationing is required. Neelakantan and Pundarikanthan (2000) presented a simulation-optimization methodology using neural network and multiple hedging rules to improve the reservoir operation performance for a drinking water reservoir system. Although the case study of their research comprised of several reservoirs, the storages of these reservoirs were lumped together into an equivalent reservoir in the mathematical model. All of the previous published papers have focused on operation of a single reservoir system, the operation for a multi-reservoir system was not considered.

CHAPTER 3 REGIONAL WATER SUPPLY OPTIMIZATION PROBLEM

Developing an optimization model to resolve a water distribution system problem requires transforming the physical system into a mathematical model. A network representation is used as the transformation approach and helps develop an optimization model. Since the guideline for operating reservoirs is crucial in operating a regional water supply system, it is very important to consider the guideline in a system optimization problem. The preliminary introduction of the guideline – rule curves and hedging rules – is stated in the subsequent section.

3.1 Network Representation

To facilitate analysis of the interrelationship between various system components, a large-scale water supply distribution system can be represented as a network structure which is a node-link combination. For instance: inflows, reservoirs, diversion structures, and demands are represented as nodes; while rivers, channels and pipes are represented as arcs (Figure 3-1). A network consists of a set of nodes linked by arcs. The benefit of using a network to reconfigure the original water supply system is the ease with which the system can be clarified and formulated by mathematical models.

In general, the optimization of a regional water distribution system can be formulated as the following minimum-cost problem:

$$Min. \sum_{t=1}^{T} \sum_{(i,j)\in \mathbf{A}} c_{(i,j),t} \cdot x_{(i,j),t} \tag{3-1}$$

$$s.t. \sum_{(j,i)\in \mathbf{A}} x_{(j,i),t} - \sum_{(i,j)\in \mathbf{A}} x_{(i,j),t} = b_{j,t} \quad , \quad \forall j \in \mathbf{N} \tag{3-2}$$

$$x_{(i,j),t}^{min} \leq x_{(i,j),t} \leq x_{(i,j),t}^{max} \quad , \quad \forall (i,j) \in \mathbf{A} \tag{3-3}$$

where

t = time index;

T = total number of time periods;

i, j = node index;

(i,j) = arc that emanates from node i and terminates at node j;

$x_{(i,j),t}$ = nonnegative flow in arc (i,j);

$x_{(i,j),t}^{min}$ = lower bound of $x_{(i,j),t}$;

$x_{(i,j),t}^{max}$ = upper bound of $x_{(i,j),t}$;

$c_{(i,j),t}$ = weighting factor (unit cost) for arc (i,j);

$b_{j,t}$ = source/sink term at node j;

$\mathbf{N}$ = node set of the network;

$\mathbf{A}$ = arc set of the network.

In this formulation, the original system elements are characterized by nodes and arcs. Each node (or arc) can represent one specific component with a corresponding physical characteristic in the system. The decision variables in the optimization model are

the directional flows in each of the arcs in the configuration. In the composite objective function, Eq. (3-1), the weighting factor for each $x_{(i,j),t}$ reflects the priority of each objective. In general, the determination of the weighting factor of each objective requires a systematic analysis of system characteristics to appropriately reflect the preference of the operator. Eq. (3-2) is the general form of a set of continuity equations which can be applied to inflow, diversion, junction, demand or reservoir nodes. Eq. (3-3) specifies the lower and upper bounds of each nonnegative flow variable.

Figure 3-1 shows a network configuration at one time period. For planning purposes, the multi-time-period analysis needs to be taken into account. In the network representation, the storage of a reservoir is represented as an arc, termed the "reservoir carry-over arc", and this arc connects two adjacent time periods in a planning horizon (Figure 3-2) to construct a large-scale network structure for optimization. Continuity at the reservoir node is maintained by the continuity equation at the node. Any nodes with a carry-over storage function other than that of reservoirs can be represented similarly. In a large-scale network structure, each node or arc at each time period is considered simultaneously with corresponding data to implement system optimization.

3.2 Reservoir Rule Curves and Hedging Rules

Figure 3-3 shows the rule curves associated with a typical multi-purpose reservoir. In this example, the three curves are the flood control curve (the upper curve), the target storage curve (the middle curve), and the firm storage curve (the lower curve).

These curves are determined at the planning stage in order to provide guidelines for operating the reservoir. Although rule curves usually remain unchanged from year to year, they can, if necessary, be updated. In general, the flood control reservation is strictly observed. During normal periods of operation, all planned demands are met at 100%, and the reservoir storage is kept at or above the established target storage level. However, during periods of drought when the reservoir storage falls below the target storage curve, the reservoir release is reduced to ensure that a sufficient amount of water remains in storage for future water supply. This situation creates a trade-off between meeting ongoing demands and maintaining adequate reservoir storage when inflow is insufficient. Using hedging rules along with the rule curves, a balance is achieved between water supply shortage and the storage objectives.

A discussion on the use of rule curves and hedging rules is provided herein. Considering that during a specific time period, if the beginning reservoir storage is greater than that of the target storage curve (in zone 3), all planned demands are met at 100%. If the beginning reservoir storage is greater than that of the firm storage curve and less than that of the target storage curve (in zone 2), the reservoir release for meeting the planned demand is reduced, for instance, by 25%; that is, the original demand is met at its 75% level. If the beginning reservoir storage is less than that of the firm storage curve (in zone 1), then the reservoir release for meeting the planned demand is reduced even further, for example, by 50%; that is, the original demand is met at its 50% level. In other words, the lower the reservoir storage zone from which water is released to satisfy the planned demand, the higher the reduction of the demand.

Figure 3-1 An Example of Water Resources Network Configuration

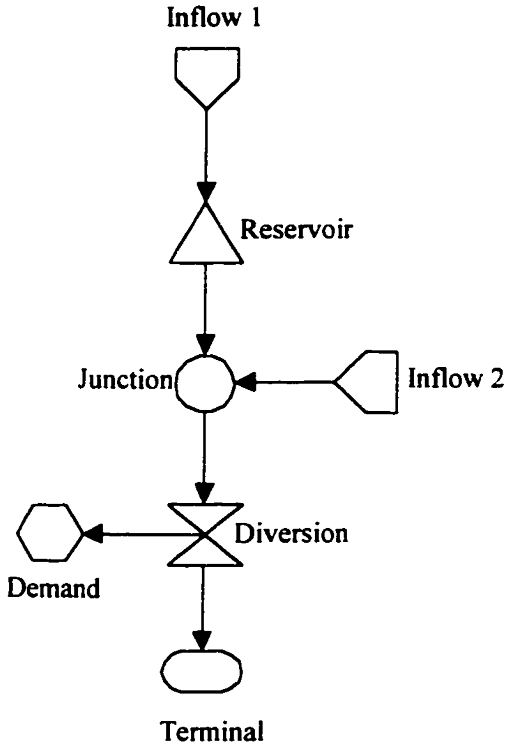


Figure 3-2 Multi-time-period Network Configuration

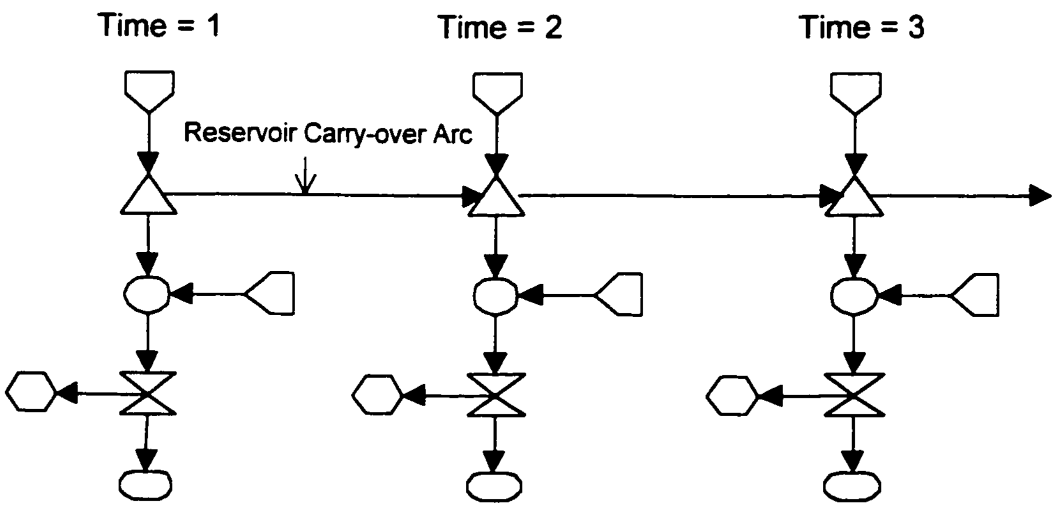
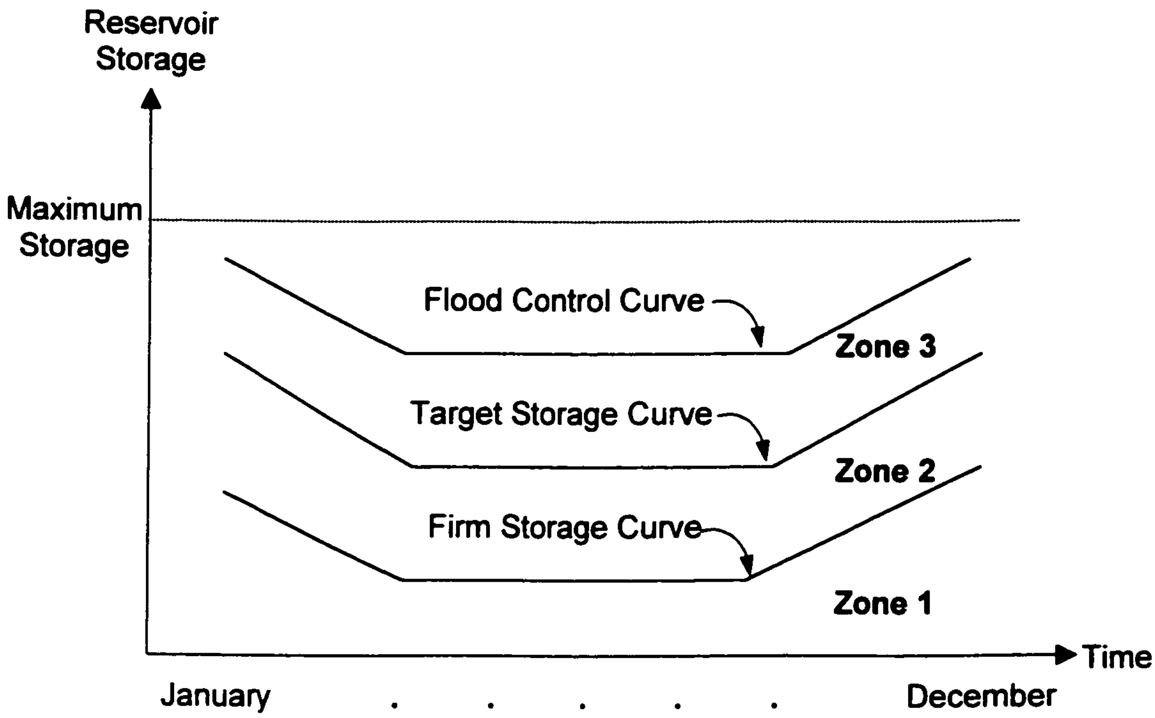


Figure 3-3 Rule Curves for a Multi-purpose Reservoir



CHAPTER 4 MIXED-INTEGER LINEAR PROGRAMMING MODEL

Sun et al. (1995) formulated a large-scale regional water supply problem in terms of an embedded generalized network flow model and discovered a solution through the use of a fast network algorithm. The model was for planning purposes, and hedging was not considered. To consider hedging, Yeh and Yang (1997) developed a network flow model in which the reservoir storage is divided into several volumes; these volumes are incorporated in the objective function as penalty terms and the associated cost coefficients are systematically determined by a sensitivity analysis. Hsu and Cheng (2002) used a similar approach and developed a network flow model for the Tanshui river basin in Taiwan. However, this approach is basically applicable to a single-time-period optimization model, and does not assure that the optimal solution of the multi-time-period model matches the rule curves and the hedging rules.

In this study, a mixed-integer linear programming (MILP) formulation is developed to incorporate the rule curves and hedging rules in a multi-purpose and multi-time-period optimization model for a regional water supply system.

4.1 Single Reservoir System

A single reservoir system is first explored with specified rule curves and hedging rules. The continuity equation for the reservoir can be written as the following:

$$S_t + I_t - O_t - E_t = S_{t+1} \tag{4-1}$$

$$S_{min,t} \leq S_t \leq S_{max,t} \tag{4-2}$$

where

S_t = beginning storage;

S_{t+1} = ending storage;

I_t = inflow during time period t;

O_t = release during time period t;

E_t = evaporation loss during time period t;

$S_{min,t}$ = minimum storage;

$S_{max,t}$ = maximum storage.

During each time period t, the relationship between the rule curves and the hedging rules is shown as a step function (Figure 4-1), which determines the preferred amount of water supply in the system. This definition is revised from Tu et al. (2002) in which the upper bound of a supply link is determined by hedging. The following equations represent the relationship:

$$\text{If } S_{min,t} \leq S_t < S_{firm,t} \text{ , then } P_t = \alpha_1 \cdot D_t \tag{4-3}$$

$$\text{If } S_{firm,t} \leq S_t < S_{targt,t} \text{ , then } P_t = \alpha_2 \cdot D_t \tag{4-4}$$

$$\text{If } S_{target,t} \leq S_t \leq S_{max,t} \text{ , then } P_t = D_t \tag{4-5}$$

where

$S_{firm,t}$ = firm storage;

$S_{target,t}$ = target storage;

D_t = planned demand;

P_t = water supply;

α_1 and α_2 = rationing factors, and $0 < \alpha_1 < \alpha_2 \leq 1$.

The rationing factors, α_1 and α_2, are determined at the planning stage, but can be modified to meet operational purposes.

In the network configuration, every demand node has a corresponding link that terminates at the demand node and the flow in the corresponding link is the water supply delivery to the demand node. Hence, the water supply variable P_t, a decision variable in the optimization model, represents the amount of water that flows into a demand node.

In the above formulation, only one of the constraints in Eqs. (4-3), (4-4), and (4-5) can be active, and the active constraint represents the actual reservoir storage and its corresponding hedging. In short, the correct solution should observe both the rule curves and the hedging rules. It is important to note that the water supply is assumed as equal to the planned demand or reduced planned demand, depending on which hedging is active.

Incorporating the reservoir rule curves and hedging rules does not cause difficulty in a simulation model (Jain et al. 1998). However, it is necessary to introduce new variables and constraints to extend Eqs. (3-1) ~(3-3) to consider hedging in an optimization model. To deal with multiple hedging rules in the optimization model, the following constraints are introduced:

$$S_t = S_{1,t} + S_{2,t} + S_{3,t} \tag{4-6}$$

$$\lambda_{1,t} \cdot S_{min,t} \leq S_{1,t} \leq \lambda_{1,t} \cdot S_{firm,t} \tag{4-7}$$

$$\lambda_{2,t} \cdot S_{firm,t} \leq S_{2,t} \leq \lambda_{2,t} \cdot S_{target,t} \tag{4-8}$$

$$\lambda_{3,t} \cdot S_{target,t} \leq S_{3,t} \leq \lambda_{3,t} \cdot S_{max,t} \tag{4-9}$$

$$P_t = \left(\lambda_{1,t} \cdot \alpha_1 + \lambda_{2,t} \cdot \alpha_2 + \lambda_{3,t}\right) \cdot D_t \tag{4-10}$$

$$\lambda_{1,t} + \lambda_{2,t} + \lambda_{3,t} = 1 \tag{4-11a}$$

$$\lambda_{1,t}, \lambda_{2,t}, \lambda_{3,t} \in \{0, 1\} \tag{4-11b}$$

where

S_t = reservoir storage, which is divided into $S_{1,t}$, $S_{2,t}$, and $S_{3,t}$ (nonnegative variables);

$\lambda_{1,t}$, $\lambda_{2,t}$, and $\lambda_{3,t}$ = binary (0-1) variables.

Eq. (4-11) ensures that only one of the λs can be active so that the reservoir storage matches the hedging rules. For example, if $\lambda_{1,t}$ is active (i.e., $\lambda_{1,t} = 1$, $\lambda_{2,t} = 0$, $\lambda_{3,t} = 0$), then only Eq. (4-7) is active, and Eqs. (4-8) and (4-9) are inactive. Therefore, the optimal solution guarantees that, if the beginning storage in time period t is in zone 1, the amount of the water supply can be obtained from Eq. (4-10) as α_1 fraction of D_t.

4.2 Multi-reservoir System

The formulation for the rule curves and hedging rules of a multiple reservoir system can be extended from the concept described above. Figure 4-2 shows a two-reservoir system (R^1 and R^2 with storages S^1 and S^2) that concurrently supplies water to one demand node (D). These two reservoirs have their own rule curves and hedging rules. The total amount of water that supplies demand node D is the summation of the waters from R^1 and R^2. Assume that the percentage from each reservoir, PE^1 and PE^2, is determined beforehand. For example, $PE^1 = 0.3$ and $PE^2 = 0.7$. In the network configuration, D can be separated into two nodes, D^1 and D^2, with their corresponding arcs, A^1 and A^2. The capacity of A^1 is equal to PE^1 fraction of A and the capacity of A^2 is equal to PE^2 fraction of A. Accordingly, the original configuration, Figure 4-2(a), can be transformed into a new configuration, Figure 4-2(b). In general, the rule curves and hedging rules for inter-relations between reservoirs can be represented by the following set of constraints:

$$S_t^k + I_t^k - O_t^k - E_t^k = S_{t+l}^k \quad , \forall k \in \mathbf{K} \qquad (4\text{-}12)$$

$$S_t^k = S_{1,t}^k + S_{2,t}^k + S_{3,t}^k \quad , \forall k \in \mathbf{K} \qquad (4\text{-}13)$$

$$P_t = \sum_{k=1}^{NK} P_t^k \quad , \forall k \in \mathbf{K} \qquad (4\text{-}14)$$

$$\lambda_{1,t}^k \cdot S_{min,t}^k \le S_{1,t}^k \le \lambda_{1,t}^k \cdot S_{firm,t}^k \quad , \forall k \in \mathbf{K} \qquad (4\text{-}15)$$

$$\lambda_{2,t}^k \cdot S_{firm,t}^k \le S_{2,t}^k \le \lambda_{2,t}^k \cdot S_{target,t}^k \quad , \forall k \in \mathbf{K} \qquad (4\text{-}16)$$

$$\lambda_{3,t}^{k} \cdot S_{target,t}^{k} \le S_{3,t}^{k} \le \lambda_{3,t}^{k} \cdot S_{max,t}^{k} \quad , \forall k \in \mathbf{K} \tag{4-17}$$

$$P_{t}^{k} = \left(\lambda_{1,t}^{k} \cdot \alpha_{1}^{k} + \lambda_{2,t}^{k} \cdot \alpha_{2}^{k} + \lambda_{3,t}^{k}\right) \cdot PE^{k} \cdot D_{t} \quad , \forall k \in \mathbf{K} \tag{4-18}$$

$$\lambda_{1,t}^{k} + \lambda_{2,t}^{k} + \lambda_{3,t}^{k} = 1 \quad , \forall k \in \mathbf{K} \tag{4-19a}$$

$$\lambda_{1,t}^{k}, \lambda_{2,t}^{k}, \lambda_{3,t}^{k} \in \{0, 1\} \quad , \forall k \in \mathbf{K} \tag{4-19b}$$

where

k = reservoir index;

K = subset of reservoirs in which the rule curves and hedging rules of each reservoir are concurrently considered;

NK = number of reservoirs in **K**;

PE^{k} = percentage of water that is supplied by reservoir k, $\sum_{k=1}^{NK} PE^{k} = 1$.

In the case of a two reservoir system shown in Figure 4-2, **K** = {R^1, R^2}, and NK = 2, and k = 1,2. The sum of the waters that supply D^1 and D^2 is the total amount of water that supplies D.

4.3 The Overall MILP Model

The summary of the steady-state, MILP model for a multi-reservoir system is described as follows:

$$Min.\sum_{t=1}^{T}\sum_{(i,j)\in\mathbf{A}} c_{(i,j),t}\cdot x_{(i,j),t} \tag{4-20}$$

$$subject\ to \quad \sum_{(j,i)\in\mathbf{A}} x_{(j,i),t} - \sum_{(i,j)\in\mathbf{A}} x_{(i,j),t} = b_{j,t} \quad , \forall j\in\mathbf{N} \tag{4-21}$$

$$x_{(i,j),t} = x^{1}_{(i,j),t} + x^{2}_{(i,j),t} + x^{3}_{(i,j),t} \quad , \quad \forall (i,j)\in\mathbf{A}_R \ , \ \forall j\in\mathbf{N}_{RI} \tag{4-22}$$

$$x_{(i,j),t} = \sum_{k=1}^{NK} x^{k}_{(i,j),t} \quad , \forall j\in\mathbf{N}_{DI} \tag{4-23}$$

$$\lambda^k_{1,t}\cdot S^k_{min,t} \le x^1_{(i,j),t} \le \lambda^k_{1,t}\cdot S^k_{firm,t} \ , \ \forall (i,j)\in\mathbf{A}_R \ , \ \forall k\in\mathbf{K}_\mu \ , \ \forall \mu\in\mathbf{N}_{DI} \ , \ \forall j\in\mathbf{N}_{RI} \tag{4-24}$$

$$\lambda^k_{2,t}\cdot S^k_{firm,t} \le x^2_{(i,j),t} \le \lambda^k_{2,t}\cdot S^k_{target,t} \ , \ \forall (i,j)\in\mathbf{A}_R \ , \ \forall k\in\mathbf{K}_\mu \ , \ \forall \mu\in\mathbf{N}_{DI} \ , \ \forall j\in\mathbf{N}_{RI} \tag{4-25}$$

$$\lambda^k_{3,t}\cdot S^k_{target,t} \le x^3_{(i,j),t} \le \lambda^k_{3,t}\cdot S^k_{max,t} \ , \ \forall (i,j)\in\mathbf{A}_R \ , \ \forall k\in\mathbf{K}_\mu \ , \ \forall \mu\in\mathbf{N}_{DI} \ , \ \forall j\in\mathbf{N}_{RI} \tag{4-26}$$

$$x^k_{(i,j),t} = \left(\lambda^k_{1,t}\cdot\alpha^k_1 + \lambda^k_{2,t}\cdot\alpha^k_2 + \lambda^k_{3,t}\right)\cdot PE^k_j\cdot D_{j,t} \ , \ \forall k\in\mathbf{K}_j \ , \ \forall j\in\mathbf{N}_{DI} \tag{4-27}$$

$$\lambda^k_{1,t} + \lambda^k_{2,t} + \lambda^k_{3,t} = 1 \ , \ \forall k\in\mathbf{K}_j \ , \ \forall j\in\mathbf{N}_{DI} \tag{4-28a}$$

$$\lambda^k_{1,t}, \lambda^k_{2,t}, \lambda^k_{3,t} \in \{0,1\} \ , \ \forall k\in\mathbf{K}_j \ , \ \forall j\in\mathbf{N}_{DI} \tag{4-28b}$$

$$x^{min}_{(i,j),t} \le x_{(i,j),t} \le x^{max}_{(i,j),t} \quad , \quad \forall (i,j)\in\mathbf{A} \tag{4-29}$$

where

$\mathbf{A}_R$ = subset of $\mathbf{A}$ for reservoir carry-over storage arcs;

$\mathbf{N}_{RI}$ = subset of $\mathbf{N}$ for reservoirs that have rule curves;

$\mathbf{N}_{DI}$ = subset of $\mathbf{N}$ for demand nodes subject to hedging rules;

$\mathbf{K}_j$ (or $\mathbf{K}_\mu$) = subset of reservoirs that supply demand node j (or node μ);

$D_{j,t}$ = planned demand for demand node j;

NK = number of reservoirs in $\mathbf{K}_j$;

PE_j^k = percentage of the total water supply from reservoir k to demand node j,

$$\sum_{k=1}^{NK} PE_j^k = 1;$$

$\lambda_{1,t}^k$, $\lambda_{2,t}^k$, and $\lambda_{3,t}^k$ = binary (0-1) variables for reservoir k;

$S_{min,t}^k$ = minimum storage of reservoir k;

$S_{firm,t}^k$ = firm storage of reservoir k;

$S_{target,t}^k$ = target storage of reservoir k;

$S_{max,t}^k$ = maximum storage of reservoir k;

α_1^k and α_2^k = rationing factors for reservoir k; and all other variables are as defined before.

Eqs. (4-22) ~ (4-28) ensure that the rule curves and hedging rules are observed in a multi-reservoir setting. Eq. (4-29) specifies the upper and lower bounds of each flow variable; for example this equation can represent the link capacity limitation, water supply limitation or reservoir storage limitation. The nonnegative decision variables include the flow and binary variables.

It is important to note that the determination of k and $\mathbf{K}j$ depends on the particular demand node j under consideration. For example, if demand node 1 can receive water from reservoirs 1 and 2, then k varies from 1 to 2, and $\mathbf{K}_1$ contains {R^1, R^2} for demand node 1. In this example, we have $PE_1^1 + PE_1^2 = 1$. Likewise, if demand node 2 can receive water from reservoirs 3, 4 and 5; then, k =1 stands for reservoir 3, k =2 stands for reservoir 4, and k =3 stands for reservoir 5, and $\mathbf{K}_2$ contains {R^3, R^4, R^5} for demand node 2. In this example, it is obvious that $PE_2^1 + PE_2^2 + PE_2^3 = 1$.

4.4 Solution Methodology

There are several approaches for solving an MILP problem, but the most popular approach uses the branch-and-bound algorithm. With the branch-and-bound algorithm, the original problem is recursively decomposed into smaller problems to construct a tree of subproblems. These subproblems are systematically explored with the feasible integer solution and corresponding objective bounds to reach the optimal solution. The details of the branch-and-bound algorithm can be found in Nemhauser and Wolsey (1988) and Wolsey (1998).

4.5 Numerical Example

The following two-reservoir hypothetical simplified water distribution system is used to demonstrate the applicability and capability of the presented MILP model.

System Description

Figure 4-3 shows the configuration of this simplified water supply system. In this system, there are two supply sources, two reservoirs (RE1 and RE2), two demand nodes (DD1 and DD2), two diversion nodes, two terminal nodes and nine arcs. The water from the upstream sources flow into the reservoirs, and then the water will be stored or released to supply downstream demand nodes. Thus reservoirs play very important roles

in operating this system in order to determine the optimal water supply. To consider multi-time-period operation, each reservoir carry-over arc connects two adjacent time periods in a planning horizon to construct a large-scale water distribution network structure.

Assuming that the planning horizon has 12 time periods. The inflow data of each inflow node used is shown in Table 4-1. The maximum storage of RE1 is 50 units and the maximum storage of RE2 is 30 units. The initial storage of RE1 is 35 units and the initial storage of RE2 is 25 units. Each reservoir has two corresponding rule curves and rationing factors (Table 4-2 and 4-3, and Figure 4-4). The rule curves are on a 12-time-period basis. The water demand of DD1 is 10 units and that of DD2 is 20 units in each time period. The maximum capacity of each arc is 100 units. Therefore, the capacity limitation is not a restricting factor for water delivery.

The interpretation of the rule curves and of the hedging rules for reservoir RE1 is as follows:

1. If the beginning storage is greater than that of the target curve, the planned demand at each demand node is met at 100%.
2. If the beginning storage is greater than that of the firm curve and less than that of the target curve, the planned demand for the demand node is met at 70%.
3. If the beginning storage is less than that of the firm curve, the planned demand for the demand node is met at 50%.

The interpretation of the rule curves and of the hedging rules for reservoir RE2 is as follows:

1. If the beginning storage is greater than that of the target curve, the planned demand at each demand node is met at 100%.
2. If the beginning storage is greater than that of the firm curve and less than that of the target curve, the planned demand at each demand node is met at 80%.
3. If the beginning storage is less than that of the firm curve, the planned demand for each demand node is met at 60%.

In the network configuration, demand node DD1 can receive water from reservoir RE1 and demand node DD2 can receive water from reservoir RE1 and RE2. Water supplies to these two demand nodes are required to satisfy the hedging rules in the optimization. Since DD2 can obtain waters from RE1 and RE2, in this case, assume 50% of total water supplying DD2 is required from RE1 and 50% is from RE2. Therefore, DD2 can be divided into two demand nodes, $DD2^1$ and $DD2^2$ with 10 units of water as planned demand respectively (Figure 4-5), then the above-mentioned overall MILP model can be implemented to optimize the system operation with hedging requirements.

MILP Model

The two hypothetical competing objectives considered in this case are: (1) maximization of water supply for the demand nodes; and (2) maximization of reservoir storage. The weighting method is used to combine the two objectives in the objective

function to reflect their relative importance. The weighting factors of water supply and reservoir storage are assumed 1 and 0.0001, respectively. In this situation, the priority of water supply is higher than that of the reservoir storage function.

The maximization optimization problem can be converted to a standard minimum-cost problem by multiplying the objective function with a minus sign. Consequently, the 12-time-period MILP model for the simplified system can be formulated as follows:

$$Min. \sum_{t=1}^{12} \left\{ -\sum_{\substack{j \in \mathbf{N}_{DI} \\ (i,j) \in \mathbf{A}}} (C_D)_{j,t} x_{(i,j),t} - \sum_{\substack{j \in \mathbf{N}_{RI} \\ (i,j) \in \mathbf{A}_R}} (C_R)_{j,t} x_{(i,j),t} \right\} \tag{4-30}$$

$$s.t. \qquad x_{(j,t),t} = IN_{j,t} \quad , \quad \forall j \in \mathbf{N}_I \tag{4-31}$$

$$\sum_{(j,i) \in \mathbf{A}} x_{(j,i),t} - \sum_{(i,j) \in \mathbf{A}} x_{(i,j),t} = 0 \quad , \quad \forall j \in \{\mathbf{N}_G \cup \mathbf{N}_{Div}\} \tag{4-32}$$

$$\sum_{(j,i) \in \mathbf{A}} x_{(j,i),t} - \sum_{(i,j) \in \mathbf{A}} x_{(i,j),t} + Y = 0 \quad , \quad \forall j \in \mathbf{N}_R \tag{4-33}$$

$$Y = x_{(i,j),t+1} - x_{(i,j),t} \quad , \quad \forall (i,j) \in \mathbf{A}_R \quad , \quad \forall j \in \mathbf{N}_R \tag{4-34}$$

Eqs. (4-22)~(4-29)

where

$\mathbf{N}_I$ = subset of $\mathbf{N}$ for inflow nodes;

$\mathbf{N}_G$ = subset of $\mathbf{N}$ for junction nodes;

$\mathbf{N}_{Div}$ = subset of $\mathbf{N}$ for diversion nodes;

$IN_{j,t}$ = amount of inflow to inflow node j;

C_D = unit cost of supply to demand node;

C_R = unit cost of storage arc of the reservoir.

The multi-objective function is formulated by Eq. (4-30). The continuity for the inflow, junction, diversion and reservoir nodes are denoted by Eqs. (4-31)~(4-34), respectively. In the optimization model, there are 344 decision variables, including 66 integer variables and 370 constraints. Because the initial storage of RE1 and RE2 is assumed in zone 2, the integer variables for the beginning of the first time period does not need to be evaluated and the corresponding water supply for DD1 and DD2 is already pre-determined in the optimization model.

In this study, the MILP optimization problem is solved with a commercial optimization program, LINGO. LINGO is capable of solving linear, nonlinear and integer programming problems. LINGO uses the branch-and-bound algorithm to deal with the integer variables. The details of LINGO are described in the LINGO 6.0 user's guide (1999).

Using LINGO to solve this MILP model, the optimization results are shown in Table 4-4. The objective function value of the MILP model is –266.0. The results indicate that the reservoir storage and water supply simultaneously satisfy the rule curves and the hedging rules. For example, the solution shows that the beginning storage of reservoir RE1 at the second time period is in zone 2, and the corresponding optimal water supply for DD1 and DD2[1] is 7 units and thus meets the second hedging rule. Consequently, the capability of the proposed MILP model in handling hedging rules for reservoir operation in a water distribution system is verified by the above illustrative example. In addition, the results demonstrate that the main function of hedging for

reservoir operation is to utilize water more efficiently during a drought (i.e. conditionally restrain the current water uses for future water supply) and thus reduce the impact of drought to water users.

Table 4-1 Water Sources (Unit) of the Simplified System

Source	Time Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	10	10	10	12	12	12	14	14	14	8	8	8
2	8	8	8	10	10	10	12	12	12	10	10	10

Table 4-2 Rule Curves (Unit) Used in the Simplified System

Time	RE1		RE2	
	Firm Curve	Target Curve	Firm Curve	Target Curve
1	30	50	20	30
2	27	47	17	27
3	24	44	14	24
4	21	41	11	21
5	18	38	8	18
6	15	35	5	15
7	15	35	5	15
8	18	38	8	18
9	21	41	11	21
10	24	44	14	24
11	27	47	17	27
12	30	50	20	30

Table 4-3 Hedging Rules Used in the Simplified System

Reservoir Storage	Rationing Factor	
	RE1	RE2
Minimum Storage $\leq S_t <$ Firm Storage	50%	60%
Firm Storage $\leq S_t <$ Target Storage	70%	80%
Target Storage $\leq S_t \leq$ Maximum Storage	100%	100%

S_t : Beginning storage of RE1 (or RE2) in time period t.

Table 4-4 The MILP Model Results of the Simplified System

Time	Water Supply			Reservoir Beginning Storage			
	DD1	DD2		RE1		RE2	
		DD2[1]	DD2[2]	Storage	Zone	Storage	Zone
1	7	7	8	35	2	25	2
2	7	7	8	31	2	25	2
3	7	7	8	27	2	23	2
4	7	7	10	23	2	24	3
5	7	7	10	21	2	24	3
6	7	7	10	19	2	24	3
7	7	7	10	17	2	24	3
8	5	5	10	17	1	26	3
9	5	5	10	20	1	28	3
10	7	7	10	25	2	30	3
11	5	5	10	19	1	30	3
12	5	5	10	17	1	30	3

Figure 4-1 Rule Curves and Hedging Rules Represented by a Step Function

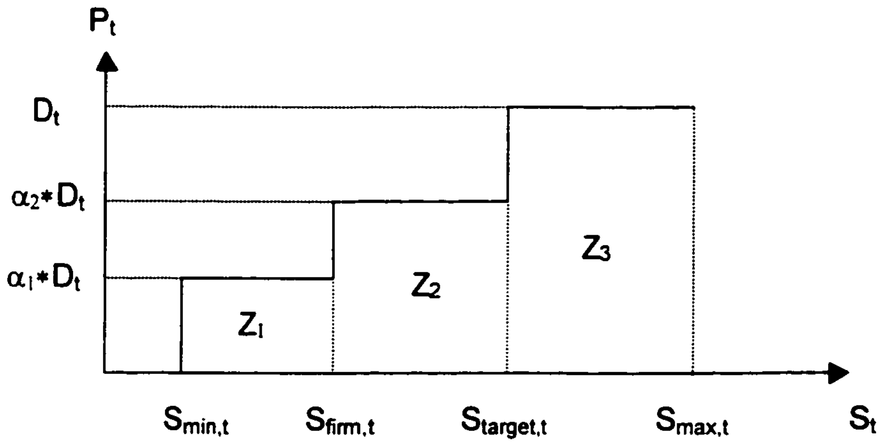
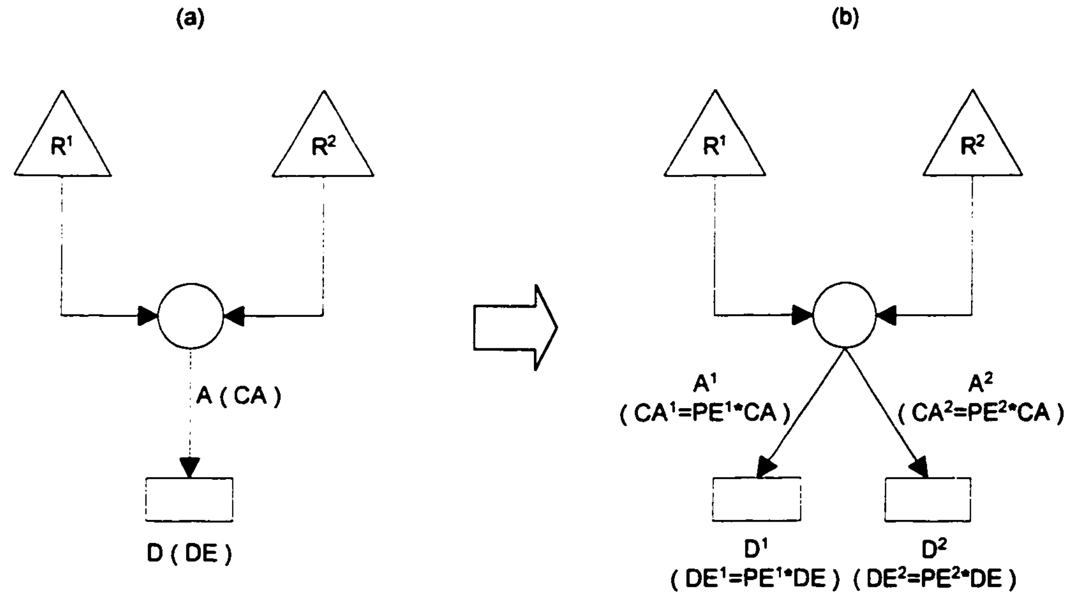


Figure 4-2 Rule Curves and Hedging Rules for a Multi-reservoir System



CA : Capacity of arc A
DE : Planned demand of demand node D

CA^1 : Capacity of arc A^1
CA^2 : Capacity of arc A^2
DE^1 : Planned demand of demand node D^1
DE^2 : Planned demand of demand node D^2

$0 \le PE^1 \le 1, 0 \le PE^2 \le 1$

$PE^1 + PE^2 = 1$

Figure 4-3 Schematic of Simplified System

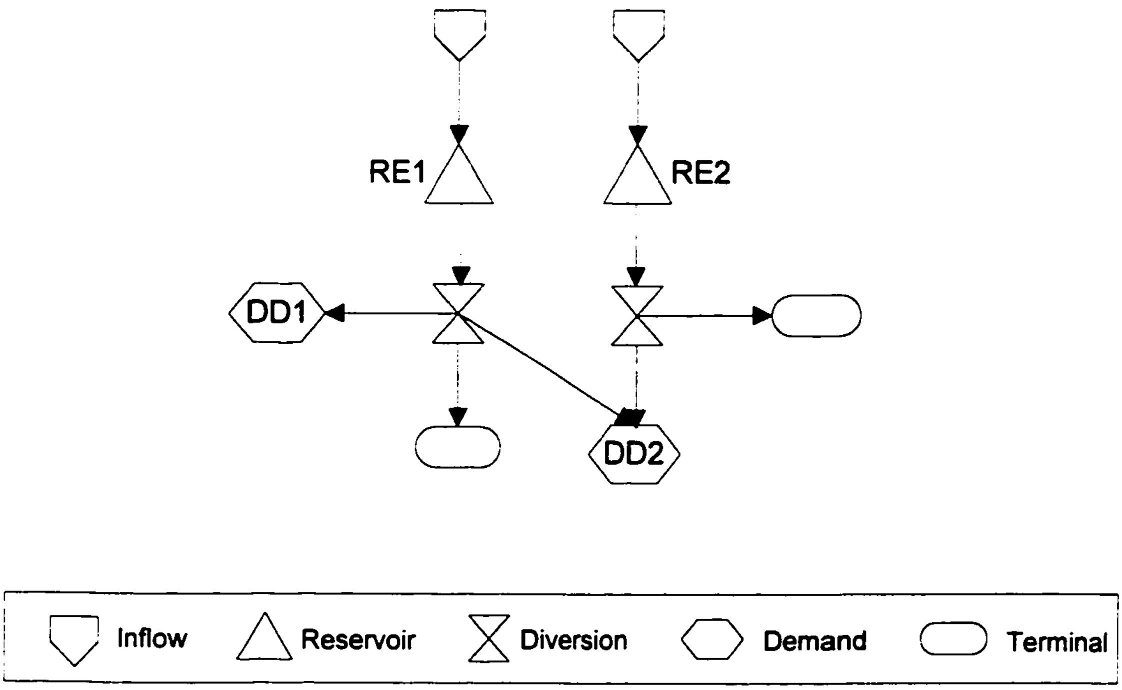
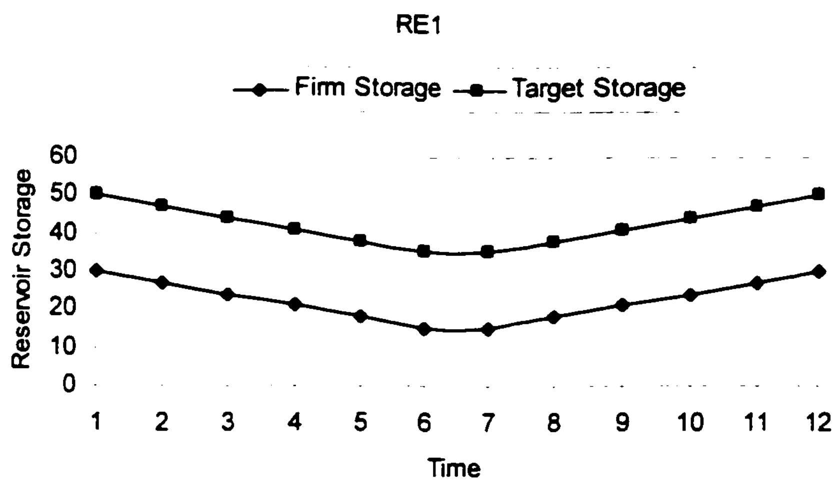


Figure 4-4 The Rule Curves Used in the Simplified System



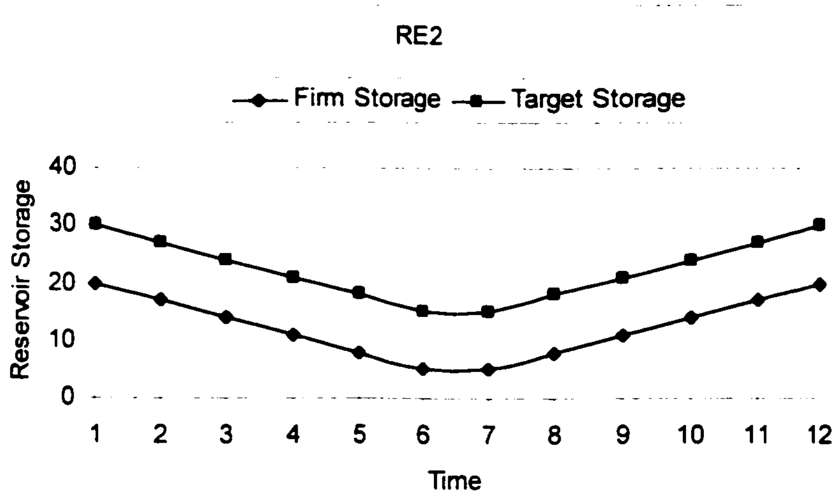
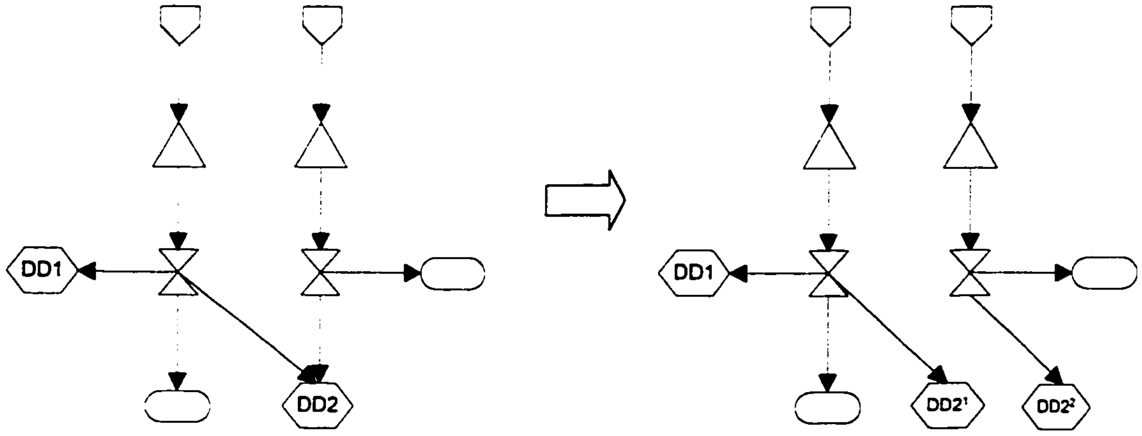


Figure 4-5 Configuration Transformation for the Simplified System



CHAPTER 5 MIXED-INTEGER NONLINEAR PROGRAMMING MODEL

In general, the reservoir rule curves and hedging rules are pre-determined in the planning stage. However, during the reservoir operation, the sediment gradually changes the water storage of a reservoir and the population and economic growth in the reservoir serving area usually increases demands on the water supply. As a result, it is necessary to evaluate and modify the current reservoir rule curves and hedging rules to improve reservoir operation performance in a regional water distribution system.

Chen (1995) developed a methodology incorporating genetic algorithms to modify rule curves for a single reservoir system. The results showed that the shape of rule curves was in oscillatory distribution and difficult to follow for real practice. Shih and ReVelle (1995) proposed a mixed integer-programming model to determine the optimal volumes of reservoir storage plus anticipated inflow that triggered several phases of hedging for reservoir operation during drought periods. Their model was applied for a single reservoir system. Neelakantan and Pundarikanthan (2000) presented a neural network-based simulation-optimization methodology to find the optimal reservoir storage levels for hedging. Although the case study of their research comprised of several reservoirs, the storages of these reservoirs were lumped together in the mathematical model. All the studies above have only considered obtaining the optimal reservoir

storages in order to use hedging rules for single reservoir systems. The rationing factors were pre-determined as given values in these models.

This present study focuses on modifying both the current rules curves and hedging rules for multi-reservoir systems. Preferably, actual reservoir operation will easily follow the shape of the new rule curves which are obtained.

Examining the overall MILP model described in Chapter 4, Eqs. (4-24)~(4-27) are linear constraints with given rule curves and rationing factors, and the binary variable set is one subset of decision variables. If the reservoir rule curves and hedging rules need to be evaluated, the rule curves and rationing factors become unknown and these linear constraints change to bilinear constraints, which are nonlinear. The nonlinearity is caused by the multiplication of one rule curve variable (or rationing factor variable) and one binary variable. Thus the original MILP model will change to a mixed-integer nonlinear programming (MINLP) model, which is a nonconvex optimization problem and is difficult to resolve.

The general formulation of a MINLP problem with binary variables can be posed as (Floudas, 1995):

$$\underset{x,y}{Min.}\ f(\boldsymbol{x},\boldsymbol{y}) \tag{5-1}$$

$$s.t.\quad h(\boldsymbol{x},\boldsymbol{y}) = 0 \tag{5-2}$$

$$g(\boldsymbol{x},\boldsymbol{y}) \leq 0 \tag{5-3}$$

$$\boldsymbol{x} \in \boldsymbol{X} \subseteq \boldsymbol{R}^{n} \tag{5-4}$$

$$\boldsymbol{y} \in \boldsymbol{Y} = \{0,1\}^{q} \tag{5-5}$$

where

$\boldsymbol{x}$ = a vector of n continuous variables;

$\mathbf{y}$ = a vector of q binary (0-1) variables;

$f(\boldsymbol{x},\boldsymbol{y})$ = objective function;

$h(\boldsymbol{x},\boldsymbol{y})$ = equality constraints;

$g(\boldsymbol{x},\boldsymbol{y})$ = inequality constraints.

A MINLP problem is a NP-complete problem (Nemhauser and Wolsey, 1988) which consists of the continuous domain and the combinatorial domain. The presence of these two domains causes the complexity of this problem and creates the difficulties in solving it. To determine the global optimum of the MINLP problem in the nonconvex domain, which may consists of a number of local optimums, is NP-hard (Murty and Kabadi, 1987).

5.1 Solution Methodologies for Solving MINLP Models

To handle the MINLP problems, several types of methods had been reported in the past. These methods are: (1) combination method; (2) decomposition methods; (3) approximation methods; (4) heuristic combinatorial optimization methods; and (5) other methods. The following will investigate the mathematical characteristics of these methods and illustrate a number of application examples.

Combination Method

As to solving a MINLP model, the intuitive manner is to use a combination methodology, which consists of a nonlinear programming (NLP) method and the branch-and-bound method. The basic idea of this combination method is to solve one NLP problem in each branch of the "tree" and proceed with this process until the final optimum is reached. In general, it is difficult to obtain the optimum by implementing this methodology because numerous branches along with their corresponding NLP problems need to be evaluated to finally achieve the optimal solution. If the dimension of one NLP problem or the integer variable set is large, the efficiency of this methodology is doubtful. In addition, the optimal solution obtained from this methodology can not be guaranteed as a global optimum at the nonconvex domain.

Kim and Mays (1994) proposed an MINLP model for minimizing the cost to rehabilitate and replace pipes in a water distribution system. This model was solved by a combination scheme involving a branch-and-bound algorithm and a generalized reduced gradient method. In their research, for cases with large number (say >1000) of possible combinations, 1000 possibilities were randomly selected to represent the whole search domain. Because of the nonlinear characteristic and the possibility of numerous branch searching, this methodology may not be suitable to solve large-scale MINLP problems and the solution may be the local optimum.

Decomposition Methods

The fundamental idea of the decomposition methods is to seek the upper bounds and lower bounds of the objective function value of a MINLP optimization problem. The optimal solution can be obtained by the convergence of upper bounds and lower bounds. The original problem is divided into two subproblems: the primal problem and the master problem. The solution information of the primal problem can provide the nonincreasing upper bounds. The solution information of the master problem can contribute to finding the nondecreasing lower bounds. Theoretically, with a limited number of iterations between solving the primal problems and master problems, the global optimal solution can be achieved by the convergence of the upper bounds and lower bounds.

Two popular decomposition methods used to solve MINLP optimization problems are the Generalized Benders Decomposition (GBD) method and the Outer Approximation (OA) method. Floudas (1995) reported an excellent introduction describing GBD (and variants) and OA (and variants) for dealing with MINLP problems. The introductions of GBD and OA will be briefly described in the following sections.

Generalized Benders Decomposition (GBD) Method

Benders (1962) developed a decomposition method for the solution of mixed-variables programming problems. In 1972, Geoffrion generalized Benders' decomposition approach to obtain the optimal solution for certain nonconvex NLP and

MINLP problems. In the GBD algorithm, the upper bound of optimal solution and Lagrange multipliers associated with equality and inequality constraints are obtained from the primal problem in which the complicating variables are fixed. By fixing the complicating variables, it becomes easier to solve the original problem. For instance, the integer variables in a MINLP problem can be the complicating variables. The master problem is developed based on the nonlinear duality theory involving the Lagrange multipliers that are resulted from the primal problem. The new set of complicating variables is obtained after solving the master problem and used in the next primal problem as fixed variables. Proceeding with the iteration between the primal problem and master problem the optimal solution can be achieved by the convergence of upper bounds and lower bounds. Bagajewicz and Manousiouthakis (1991) reported an analysis on various implementations of GBD and arrived at several conclusions.

Jacobs et al. (1995) reported a stochastic optimization model to deal with the optimal scheduling of hydropower generation problem for a multi-reservoir system. The model was conducted based on network formulation and solved by GBD. The authors found that the performance of GBD in computing efficiency was very encouraging in solving this kind of problem.

Cai et al. (2001) applied GBD to solving two large nonconvex water resources optimization problems. In their model formulation, the elastic slack variables were introduced and incorporated in the objective function as penalty terms to guarantee the feasibility of the primal problem. Compared with two NLP solvers, MINOS (Murtagh and Saunders, 1982) and CONOPT (Drud, 1994), the authors found that GBD could

obtain similar objective function value in less run time if the complicating variables were carefully selected.

Outer Approximation (OA) Method

The concept of OA was originally proposed by Gomory(1958, 1960), Cheney and Goldstein(1959), and Kelley (1960). Duran and Grossmann (1986a,b) presented the OA algorithm to solve certain MINLP problems. The basic procedure of OA is similar to GBD except for the derivation of the master problem. In the OA algorithm, the master problem is derived using the solution of the primal problem and outer linearizations of the nonlinear functions around the solution of the primal problem.

Karatzas and Pinder (1993) presented a methodology in which the OA method was incorporated to deal with the groundwater quantity management problem. Since the fixed charges were formulated as an exponential term in the objective function, the resulting problem was a concave minimization problem. Two examples were presented to demonstrate the efficiency and robustness of this methodology in finding the global optimal solution.

Watkins and McKinney (1998) used GBD and OA algorithms to solve special water resources MINLP problems in which discrete and nonlinear terms were in the cost functions, and then compared the performance of these two algorithms. Although it was difficult to claim which one of these two algorithms was better, the authors suggested that GBD may be better suited for dealing with larger scale planning problems.

Approximation Methods

The primary difficulty for solving a MINLP problem is due to the combinatorial characteristic caused by the discontinuous/integer variables. One way to eliminate this obstacle is to use continuous variables to approximate the discontinuous variables to obtain a continuous search domain. Thus the original MINLP model can be converted into a nonlinear programming (NLP) problem, which can be solved by conventional nonlinear programming algorithms.

Two approximation methods proposed in the water resources field, especially in the groundwater management area, are: (1) the penalty coefficient (PC) method, which includes the polynomial penalty coefficient (PPC) method and the exponential penalty coefficient (EPC) method, and (2) the pseudo-integer (PI) method. Note that using these approximation methods may create a complex nonlinearity in the resulting NLP problem and the optimal solution may be the local optimum, but is not assured to be the global optimum.

Mckinney and Lin (1995) reported a groundwater MINLP model to deal with the optimal aquifer remediation design problem. In their formulation, the binary variables were involved in the objective function. They used PPC method to approximate the binary variables to convert the original MINLP problem into a NLP problem. Compared with PI and EPC method, the authors claimed that the model performance of PPC was better than PI and EPC in solving MINLP optimal remediation design problems.

Heuristic Combinatorial Optimization Methods

In an optimization problem, if the discrete decision variables are involved and a solution is searched in a finite set of possible solutions to meet the optimum, this optimization problem is a combinatorial optimization problem. Searching for the global optimal solution of a combinatorial optimization problem is a challenging task. As a result, a number of heuristic search methods, such as Genetic Algorithms (GA) and Simulated Annealing (SA), are proposed to solve combinatorial optimization problems. What these methods have in common is the lack of a gradient mathematical characteristic. The following will briefly summarize the concept of GA and SA and report some example applications.

Genetic Algorithms (GA)

GA was originally developed by Holland in 1975. Motivated from biological evolution, GA uses a set of analogous process and operators: selection, crossover, mutation, reproduction, and replacement, to search for a global or near-global optimal solution of a complex optimization problem. Unlike the traditional gradient-based algorithms, the derivatives are not required in GA. A population of starting chromosomes that are randomly generated to represent a set of initial solutions goes through the GA process and operations and improves the objective value generation by generation. By evolving chromosomes without the necessity of gradient evaluations, GA has the ability

to jump out of local optima and achieve the global optimum. Readers can see Goldberg (1989) for a comprehensive introduction of GA.

Ritzel and Eheart (1994) presented the application of GAs on a multiple objective groundwater pollution containment problem. Finding the optimal solutions on the trade-off curve between the reliability and cost of a hydraulic containment system was the main task in their research. Compared with the mixed-integer chance constrained programming, the results obtained from their example study showed that GA could obtain similar or better optimal solution with less computer time.

McKinney and Lin (1994) reported a methodology in which groundwater models and GAs were combined to solve three complicated groundwater management problems: maximum pumping from an aquifer, minimum cost of water supply development, and minimum cost of aquifer remediation. The application results showed that the performance of GA was as good as or superior to that obtained by LP and NLP. In addition, GA was verified as having the ability to efficiently search for the global or near-global optimal solution of those groundwater management and design problems.

Oliveira and Loucks (1997) presented a methodology incorporating GA to derive multireservoir operating policies. The operating policies can indicate the total release of reservoirs, the individual reservoir storage targets, and the existing total storage volume in the system. In their approach, a simulation model was used to evaluate each generated operating policy in GA. The process of updated policy generation and evaluation proceeded until the stopping criterion was met. The applicability of this methodology was demonstrated by two hypothetical reservoir systems.

For more on water resources GA applications, readers are referred to Goldberg and Kuo (1987), Simpson et al. (1994), Halhal et al. (1997), Savic and Walters (1997), Montesinos et al. (1999), and Cai et al. (2001).

Simulated Annealing (SA)

SA was first proposed by Kirkpatrick et al. (1983). This algorithm was inspired from a physical process of thermodynamics, in which a substance is heated and then slowly cooled to obtain a strong crystalline structure. In SA, a new state of a system is constructed by random displacement. During the cooling procedure, if the energy of the current state is lower than that of the previous state, the change is accepted unconditionally and the system is updated. If the energy of the current state is greater than that of the previous state, the new state is accepted probabilistically by the Metropolis criterion. Thus SA has the ability to reach the global optimum or near-global optimum instead of trapping in the local optimum.

Dougherty and Marryott (1991) reported the application of SA on the optimization of groundwater management problems. The mathematical characteristics of SA were examined and investigated. By four illustrative applications of SA, the authors claimed that SA was flexible and had the potential for solving combinatorial groundwater management problems.

Unlike the conventional optimization methods used in the past (e.g., linear programming, nonlinear programming, and dynamic programming), a SA-based

approach was proposed by Cunha and Sousa (1999) to deal with the optimal water distribution design problem. Compared with the solutions of past well-known studies, the authors claimed that their approach could provide solutions with high quality for network design problems.

For more on water resources SA applications, readers are referred to Marryott et al. (1993), Mauldon et al. (1993), Loganathan et al. (1995), Zheng and Wang (1996), and Skaggs et al. (2001).

Other Methods

The other methods include several heuristic approaches for some specific problems. In literature, it is very difficult to find a robust methodology, which is universally accepted to solve MINLP problems. If there is no existing methodology that can efficiently solve a MINLP problem, a heuristic methodology is usually developed based on the special mathematical structure of this problem. Therefore, in general, one heuristic approach is only suitable to one kind of problem; this approach may not be used to deal with other problems with different mathematical structures.

Hsu and Yeh (1989) reported a heuristic approach to solve a MINLP problem for experimental design problems in groundwater hydrology. This approach was an implicit trial-and-error method based on experience to pre-choose the pumping wells before the optimization calculation. This approach took advantage of the mathematical

characteristics of their model formulation. Although this approach can efficiently solve their MINLP problem, the optimal solution was not assured as the global optimum.

Kwanyuen and Fontane (1998) presented a groundwater planning problem which considered the minimization of the installation and operation cost and was formulated as a MINLP problem using the response matrix method. In their research, a heuristic branch-and-bound method was developed based on taking advantage of the structure of the groundwater optimization problem by limiting the search process to the high potential branching only. Compared with other methods, the authors claimed that this methodology was more robust in finding the global optimal solution.

In this study, GBD, PC, PI, and SA are chosen to solve the presented MINLP model to achieve a new set of reservoir rule curves and hedging rules. In addition, a transformation technique will be proposed to solve this MINLP model as well. The results of these methods will be investigated and compared. The description of the application of these methods will be described in the following sections.

5.2 Generalized Benders Decomposition

In the GBD algorithm, a MINLP problem is divided into two subproblems: the primal problem and master problem. The idea of the primal problem is to fix the complicating variables to change the original MINLP problem into an easier problem. The primal problem can be formulated as:

$$\underset{x}{Min.}\ f(x, y^m) \tag{5-6}$$

$$s.t. \quad h(x, y^m) = 0 \tag{5-7}$$

$$g(x, y^m) \leq 0 \tag{5-8}$$

$$x \in X \subseteq R^n \tag{5-9}$$

In the primal problem, the set of complicating variables, y, is fixed in m^{th} iteration, y^m. Thus x is the only decision variable set in the primal problem and can be solved without much effort. However, since not only the feasible solution, but also the infeasible solution may occur in the primal problem, this kind of consequence will affect the derivation of the master problem.

The derivation of the master problem is based on the nonlinear duality theory. After a sequence of mathematical derivation, the master problem is transformed into a relaxed master problem. The detailed discussion of the master problem is ignored here. Readers are referred to Floudas (1995) for details. The relaxed master problem in GBD is formulated as:

$$\underset{y \in Y, \mu_B}{Min.} \quad \mu_B \tag{5-10}$$

$$s.t. \quad \mu_B \geq \xi(y; \lambda^k, \mu^k), \ k = 1,2,...,K \tag{5-11}$$

$$0 \geq \bar{\xi}(y; \bar{\lambda}^l, \bar{\mu}^l), \quad l = 1,2,...,\Lambda \tag{5-12}$$

where

μ_B = a scalar;

λ^k = optimal multiplier vectors for the equality constraints at k^{th} feasible primal problem;

μ^k = optimal multiplier vectors for the inequality constraints at k^{th} feasible primal problem;

$\bar{\lambda}^l$ = optimal multiplier vectors for the equality constraints at l^{th} infeasible primal problem;

$\bar{\mu}^l$ = optimal multiplier vectors for the inequality constraints at l^{th} infeasible primal problem;

$\xi(\mathbf{y};\lambda^k,\mu^k)$ = support function, derived from the solution of k^{th} feasible primal problem;

$\bar{\xi}(\mathbf{y};\bar{\lambda}^l,\bar{\mu}^l)$ = support function, derived from the solution of l^{th} infeasible primal problem.

As the procedure proceeds, the size of the relaxed master problem becomes larger and larger because more and more constraints associated with the solution information from the previous feasible or infeasible primal problems are added in this problem. If the optimal solution is not achieved in a small number of iterations, the efficiency of solving the resulting relaxed master problems will be doubtful.

To solve the above-mentioned MINLP problem to update the current rule curves and hedging rules, the variant 3 of GBD, v3-GBD (Floudas, 1995), which is called global optimum search (GOS) algorithm (Floudas et al., 1989), is implemented.

Different GBD variants have corresponding relaxed master problem formulation. For v3-GBD, the relaxed master problem is:

$$\underset{y\in Y,\,\mu_B}{Min.} \quad \mu_B \tag{5-13}$$

$$s.t. \qquad \mu_B \geq L(x^k, y, \lambda^k, \mu^k),\ k = 1,2,\ldots,K \tag{5-14}$$

$$0 \geq \overline{L}(x^l, y, \overline{\lambda}^l, \overline{\mu}^l), \quad l = 1,2,\ldots,\Lambda \tag{5-15}$$

where

$$L(\mathbf{x}^k, \mathbf{y}, \lambda^k, \mu^k) = f(\mathbf{x}^k, \mathbf{y}) + \lambda^{k^T} h(\mathbf{x}^k, \mathbf{y}) + \mu^{k^T} g(\mathbf{x}^k, \mathbf{y})$$
$$\overline{L}(\overline{\mathbf{x}}^l, \mathbf{y}, \overline{\lambda}^l, \overline{\mu}^k) = \overline{\lambda}^{l^T} h(\mathbf{x}^l, \mathbf{y}) + \overline{\mu}^{l^T} g(\mathbf{x}^l, \mathbf{y})$$

are the Lagrange functions associated with the optimal solution (x^k or x^l) of the primal problem.

The flowchart of v3-GBD is shown in Figure 5-1. The detailed steps of v3-GBD are:

Step 1: Select an initial y^1 with which the first primal problem is feasible. Solve the first primal problem with y^1 and obtain an optimal solution x^1 and multiplier vectors λ^1 and μ^1. Set the counters $k = 1$, $l = 0$. Let the optimal objective function value be $f(x^1, y^1)$. Set $f(x^1, y^1)$ as the current upper bound, UBD. Select a nonnegative convergence tolerance, ε.

Step 2: Solve the relaxed master problem to obtain the optimal solution y^{*} and μ_B^{*}. Set μ_B^{*} as the current lower bound, LBD. If UBD – LBD $\leq \varepsilon$, then terminate the procedure.

Step 3: Solve the primal problem with the new y set, which is y^{*}. Then the optimal solution can be either feasible or infeasible:

Step 3a: If the primal problem is feasible, set $k = k + 1$ and store the values of multipliers, λ^k and μ^k. Let the optimal objective function value be $f(x^k, y^{*})$. Update the upper

bound UBD = min{UBD, $f(x^k, y^l)$}. If UBD – LBD ≤ ε, then stop. Otherwise, return to step 2 with x^k, λ^k and μ^k.

Step 3b: If the primal problem is infeasible, set $l = l + 1$. Solve the following relaxed primal problem (Floudas et al., 1989) to obtain an optimal solution x^l and the multipliers $\overline{\lambda}^l$ and $\overline{\mu}^l$. Then return to step 2. The formulation of the relaxed primal problem is:

$$\underset{x \in X}{Min.} \quad \alpha \tag{5-16}$$

$$s.t. \quad h(x, y^l) - \alpha \le 0 \tag{5-17}$$

$$-h(x, y^l) - \alpha \le 0 \tag{5-18}$$

$$g(x, y^l) - \alpha \le 0 \tag{5-19}$$

$$\alpha \ge 0 \tag{5-20}$$

where

α = nonnegative slack variable. If α is zero, the infeasibility of the primal problem is withdrawn.

The implementation of v3-GBD will be applied to a hypothetical simplified system and the discussion will be described later.

5.3 Penalty Coefficient Methods and Pseudo-integer Method

The difficulty of solving the proposed MINLP model is due to the existence of binary variables, which are discontinuous variables. As a result, the main purpose of

implementing approximation methods is to use continuous variables to approximate binary variables. Thus, the original MINLP problem is converted into a NLP problem, which can be solved by conventional nonlinear programming algorithms.

Polynomial Penalty Coefficient (PPC) Method

The basic idea of PPC (McKinney and Lin, 1995) is to use a continuous variable and a division form to approximate the original binary variable. Let $\eta^k_{w,t}$ represent $\lambda^k_{w,t}$. Implementing PPC to approximate the binary variables of the presented MINLP model, $\eta^k_{w,t}$ can be formulated using $x^w_{(i,j),t}$:

$$\eta^k_{w,t} = \frac{x^w_{(i,j),t}}{x^w_{(i,j),t} + p} \tag{5-21}$$

where w = 1,2, and 3 and p is a very small positive value, $0<p\ll 1$. Here, $x^w_{(i,j),t}$ represents the reservoir storage variable. Introducing this formulation into Eqs. (4-24)~(4-28a), the original MINLP model will be converted to a continuous NLP model with a high degree of nonlinearity, which is caused by the multiplication terms in which the division forms are involved.

The original mathematical characteristics of the three binary variables, which specify that only one of the three zones in the reservoir can be active, can still exist by PPC. For example, let w = 1, if $x^1_{(i,j),t} = 0$, then $\eta^k_{w,t}$ = 0 and $\lambda^k_{1,t}$ = 0; if $x^1_{(i,j),t} \neq 0$, $\eta^k_{w,t}$

and $\lambda^k_{1,t}$ can be approximately considered as 1, and $\lambda^k_{2,t}$ = 0, $\lambda^k_{3,t}$ = 0, and $x^2_{(i,j),t}$ = 0, $x^3_{(i,j),t}$ = 0.

The reason of using the reservoir storage variables to approximate the integer variables is to represent the presence of which one of the three reservoir storage variables and the corresponding binary variables should be active.

Exponential Penalty Coefficient (EPC) Method

The concept of EPC (Karatzas and Pinder, 1993) is similar to PPC. A continuous variable and an exponential term are used to approximate the original binary variable. In this study, when EPC is implemented to approximate the binary variables, let $\eta^k_{w,t}$ represent $\lambda^k_{w,t}$, and $\eta^k_{w,t}$ can be formulated using $x^w_{(i,j),t}$:

$$\eta^k_{w,t} = 1 - e^{-u \cdot x^w_{(i,j),t}} \tag{5-22}$$

where w = 1,2, and 3 and u is a very large positive value. Here, $x^w_{(i,j),t}$ represents the reservoir storage variable. As a result, the original MINLP model can be transformed to a continuous NLP model with a high degree of nonlinearity, which is mainly caused by the multiplication terms in which the exponential forms are involved.

The reason for using the reservoir storage variable in EPC is the same as PPC. The original mathematical characteristics of the three binary variables, which represent that only one of the three zones in the reservoir can be active, can still exist by EPC. For

example, let $w = 1$, if $x^{1}_{(i,j),t} = 0$, then $\eta^{k}_{1,t} = 0$ and $\lambda^{k}_{1,t} = 0$; if $x^{1}_{(i,j),t} \neq 0$, $\eta^{k}_{1,t}$ and $\lambda^{k}_{1,t}$ can be approximately considered as 1, and $\lambda^{k}_{2,t} = 0$, $\lambda^{k}_{3,t} = 0$, and $x^{2}_{(i,j),t} = 0$, $x^{3}_{(i,j),t} = 0$.

Pseudo-integer (PI) Method

The concept of PI (Lall and Santini, 1989) is to introduce a continuous variable and an inequality constraint to replace the original binary variable. For the original MINLP model in this study, let $\eta^{k}_{w,t}$ represent $\lambda^{k}_{w,t}$ and introduce the following constraint:

$$\eta^{k}_{w,t} \cdot (1 - \eta^{k}_{w,t}) \leq 0 \tag{5-23}$$

where $\eta^{k}_{w,t}$ is a continuous variable, $0 \leq \eta^{k}_{w,t} \leq 1$. If $\eta^{k}_{w,t} = 0$, means $\lambda^{k}_{w,t} = 0$ in the original model; if $\eta^{k}_{w,t} = 1$, represents $\lambda^{k}_{w,t} = 1$. Therefore, the original MINLP problem becomes a NLP problem with continuos variables and constraints. Note that it may be difficult to deal with Eq. (5-23) by the conventional gradient-based method when it is preferred to obtain the 0-1 solution.

The main difference between PC and PI methods is that in the PC methods the $\lambda^{k}_{w,t}$ variables are computed as functions of the reservoir storage variables, while in the PI method the $\lambda^{k}_{w,t}$ variables are computed by the introducing continuous variables and constraints. The results of PC are either zeros or values which are almost equal to one, and the results of PI are enforced to be zeros or ones.

5.4 Simulated Annealing

Annealing is a physical process in which a solid is heated up and then slowly cooled down to reach a state with the lowest energy. At the initial high temperature, the molecules in the material have more freedom with high energy to reach different states. As the temperature is declined, the energy is decreased as well. If the material is cooled properly, the molecules will reach an ordered crystalline configuration with minimum energy. If the material is cooled rapidly, there will be defects and glass-like intrusions created inside the material. Thus, this material does not reach the state with minimum energy and ends in a polycrystalline state with higher energy. The physical scheme of SA is shown in Figure 5-2.

The SA optimization method is considered analogous to annealing: the energy represents the objective function, the configurations of molecules represents the configurations of control parameter values and decision variables, and seeking the state with lowest energy represents finding the global optimal solution.

Let s represent the solution set of a minimum optimization problem and c represent the objective function of s. In SA, a new solution (s_{i+1}) is randomly generated in the neighborhood of the current solution (s_i). As to the random generation of a new solution, readers can see Corana et al. (1987) for details. The difference between s_i and s_{i+1} is that only one element of s_i is modified. Deciding to accept s_{i+1} or not is judged by the Metropolis criterion:

If ($c_{i+1} - c_i$) ≤ 0, then accept s_{i+1};

else accept or reject s_{i+1} with the acceptance probability p: $p = exp(\frac{c_i - c_{i+1}}{T_k})$.

T_k is the current temperature after k times of temperature reduction. A pseudorandom number, pr, is generated in the range of [0,1] and compared with p. If $pr < p$, then accept s_{i+1}, otherwise reject it.

If s_{i+1} is accepted, then update the current solution with it; otherwise, keep the current solution.

Examining the Metropolis criterion, it is apparent that T_k is very important in the acceptance judgment. A higher T_k causes a higher acceptance possibility for the new solution and it implies that both uphill and downhill moving in the search domain are possible. Conversely, a lower T_k creates a lower acceptance possibility for the new solution and it implies that only downhill search is preferred to appear in the minimization problem. Based on this criterion, SA has the ability to avoid the local optimum and reach the global or near-global optimum after numerous evaluations.

A set of control parameters employed in SA is called an annealing schedule. Generally, the determination of these control parameters relies on a trial-and-error experiment to obtain an encouraging optimal solution. Among these parameters, the influential ones are: the initial temperature (T_0), the maximum number of iteration under a temperature (N_T), and the temperature reduction rate (R_T). In SA, at each temperature the simulation must proceed long enough to reach a steady state. This is called thermalization (thermal equilibrium). The parameter, N_T, which should be appropriately large, is used to reach thermalization. T_0 represents a sufficient high temperature in the

beginning of the annealing process and R_T determines how slowly this system should be cooled. Due to these characteristics, these parameters play crucial rules on deciding the performance of model convergence and the computer running time in the SA process. The stopping criteria used in SA can be decided by the user, e.g. specify a maximum number of evaluations, or assign a numerical error tolerance for the optimal solution.

A promising control parameter set in SA can guarantee a global optimization solution. However, developing an excellent parameter setting standard is a very challenging work. In literature, a number of studies are already presented to suggest the determination of SA parameters (Kirkpatrick, 1984; Aarts and Van Laarhoven, 1985; Huang et al., 1986; Corana et al., 1987; Johnson et al., 1989). Nevertheless, none of the conclusions of the studies above is guaranteed to be applicable to all SA implements. For a SA application, a systematic analysis to determine the efficient SA parameters is critical before a global optimum is claimed.

The main difficulty of solving the proposed MINLP model is because the multiplication terms of the continuous and binary variables create a high level of nonlinearity. A hybrid SA approach is developed to implement SA in solving this model to obtain a new set of rule curves and hedging rules.

The basic idea of this hybrid SA is to use SA to evaluate the complicating variables, which can be binary variables or rule curve variables, and then use an optimization solver to solve this model with given complicating variable solution. By continuing to proceed with the iteration between SA and solving this model with given

complicating solutions until the stopping criterion is met, the optimal solution can be achieved.

In this study, LINGO is used as the optimization solver. Figure 5-3 shows the flowchart of the hybrid SA approach. The steps of the hybrid SA are:

Step 1: Select a control parameter set, which includes T_0, N_T, R_T, and initial solution s_0. Calculate the objective function of s_0 by LINGO. Let $i = 1$ and $k = 0$.

Step 2: Randomly generate a new solution, s_i, and calculate the corresponding objective function by LINGO.

Step 3: Evaluate the new solution by the Metropolis criterion to decide to accept this solution or not. And update the current solution.

Step 4: Check if the total evaluation number under a constant temperature so far is equal to N_T or not. If so, reduce the temperature, the new temperature $T_{k+1} = R_T \cdot T_K$ and let $k = k+1$, then go to step 5. If not, let $i = i+1$ and go to step 2 and resume this process.

Step 5: Check if the stopping criteria are met or not. If so, terminate this process and consider that the best solution so far is the optimal solution. If not, go to step 2 and continue this process.

In this study, a SA program developed by Goffe (1994) is modified and linked with LINGO to develop the hybrid SA approach. This program is constructed based on the SA algorithm proposed by Corana et al. (1987).

5.5 Transformation

In the original MINLP problem, a product term in which a continuous variable and a binary variable are involved causes the difficulty in solving this problem. To overcome this difficulty, unlike the above-mentioned MINLP solving methods, a transformation technique (Williams, 1999) is used herein to transform the proposed MINLP problem into a MILP problem to eliminate the nonlinearity.

Assume x is a continuous variable and λ is a binary variable. Let $z = x\lambda$ and it is apparent that if $\lambda = 0$, $z = 0$, and conversely if $\lambda = 1$, $z = x$. The transformation formulations which are based on Williams (1999) are modified and stated as follows:

$$z = x_{min} \cdot \lambda + y \tag{5-24}$$

$$y - (x_{max} - x_{min}) \cdot \lambda \leq 0 \tag{5-25}$$

$$-x + y \leq -x_{min} \tag{5-26}$$

$$x - y + (x_{max} - x_{min}) \cdot \lambda \leq x_{max} \tag{5-27}$$

$$y \geq 0 \tag{5-28}$$

where

x_{min} = lower bound of x;

x_{max} = upper bound of x.

If $\lambda = 0$, then $z = 0$ which is the same as the original result. Conversely, if $\lambda = 1$ then $z = x$. Although this transformation technique creates two more continuous variables and four more linear constraints, the original MINLP problem can be transformed into a

new MILP which can be solved by any standard integer programming algorithm, e.g. the branch-and-bound method. This is the main advantage of the transformation technique.

5.6 Numerical Example

The simplified system presented in Chapter 4 is used herein to achieve a new set of rule curves and hedging rules by solving the MINLP model via the solution methodologies presented above. The MINLP model for this case study consists of Eqs. (4-22) ~ (4-29) with unknown rule curve and rationing factor variables and Eqs. (4-30) ~ (4-34). The original MINLP problem has 408 variables (including 66 binary variables) and 372 constraints (including 120 linear constraints and 252 nonlinear constraints).

Inherently, the domain to search for a new rule curve should start from the minimum reservoir storage to the maximum reservoir storage. However, according to a number of model tests, even though an encouraging objective function value can be achieved, this kind of search domain results in a set of new rule curves which are in randomly, oscillatory distribution. Thus the reservoir operators can not operate the reservoir based on the new rule curves because the shape of rule curves is difficult to follow. As a result, in this study, a set of lower bounds and upper bounds based on the current setting are assumed to obtain the new rule curves and hedging rules. Similarly, the range assumption is also applied to search for new rationing factors to avoid a large difference between α_1 and α_2.

For this simplified system, the lower bound of each value of each rule curve is assumed as the original value minus 2 units. The upper bound of each value of each rule curve is assumed as the original value plus 2 units. If the upper bound is equal to or greater than the maximum storage of reservoir, the upper bound is set as the maximum storage. The lower bound of α_1 is assumed as the original value minus 0.1. The upper bound of α_2 is assumed as the original value plus 0.1. The searching ranges for new rule curves and rationing factors are shown in Table 5-1 and 5-2.

The implementations of the MINLP solution methodologies are described and the results are discussed in the following sections. In these methodologies, LINGO is used as a solver to handle an optimization problem.

Generalized Benders Decomposition

Solving the MINLP model by GBD, the binary variables are chosen as the complicating variables. As a result, the primal problem is an LP problem and the relaxed master problem is a MILP problem. In each primal problem, the continuous decision variables include the water flows in this network system, the reservoir rule curves and the rationing factors. In the relaxed master problem, only one continuous variable is involved and the other decision variables are binary variables.

According to the GBD algorithm, the initial binary variable guess must allow the first primal problem to be feasible. After a number of tests, a good initial integer guess is achieved: for each reservoir, the storage at the first 7 time periods is specified in zone 2,

i.e. $\lambda_{1,t}^{k} = 0$, $\lambda_{2,t}^{k} = 1$ and $\lambda_{3,t}^{k} = 0$, t = 1~7, and the storage at the rest of the time periods is specified in zone 1, i.e. $\lambda_{1,t}^{k} = 1$, $\lambda_{2,t}^{k} = 0$ and $\lambda_{3,t}^{k} = 0$, t = 8~12. Here, the nonnegative convergence tolerance, ε, is assumed as 0.01.

In each primal problem, there are 336 continuous variables and 360 linear constraints. In each relaxed master problem, there is one continuous variable and 66 binary variables. The number of constraints is varied because one more constraint is added after one primal problem is solved.

After a number of iterations between the primal and relaxed master problems, this study found that the convergence of the upper bounds and lower bounds is extremely slow. This is mainly because:

1. From the mathematical viewpoint, in each iteration, the model would like to minimize the objective function value of the relaxed master problem to be as small as possible. Therefore, based on the formulation of the relaxed master problem, the optimization model would provide as many $\lambda_{3,t}^{k} = 1$ solutions as possible. This situation implied that the model would prefer the reservoir storage solution of each time period to be in zone 3. If the sources were plentiful, this situation may not generate an infeasible primal problem. However, this situation created infeasibility in the primal problem when the sources were not plentiful. Because the main purpose of incorporating reservoir rule curves in reservoir operation is to provide operating guidelines for drought periods; thus, the $\lambda_{3,t}^{k} = 1$ solution was not the preferable result. This is a conflict situation between the physical system and the mathematical model.

2. The upper bound values kept as constant, which was the objective function value of the first feasible primal problem. Examining the primal problem of each iteration, most of the primal problems were infeasible, i.e., most of the binary solution of the previous relaxed master problem caused the infeasibility in the next primal problem. Thus a number of relaxed primal problems with artificial slack variables needed to be solved.
3. The order of the range of objective function values of both primal and relaxed master problem was 10^2. Although the lower bound values increased in each iteration, the general improvement performance of lower bounds was in an order of 10^{-3}. In addition, a number of results showed that the lower bounds kept nonincreasing. This condition implied that the convergence of the upper bounds and lower bounds was extremely slow and that the number of iteration runs might be multitudinous.
4. As the iteration procedure proceeded, the size of the relaxed mastered problem became larger and larger because one additional constraint, in which most of the binary variables were involved, was added after one primal problem was solved. Thus the solving time became longer as well to solve a relaxed master problem in each iteration. This kind of condition resulted in space and memory problems when running the model on a PC.

Although GBD was demonstrated as a suitable methodology in dealing with nonconvex water resources management problems in literature (Watkins and McKinney, 1998; Cai et al., 2001), in this study, unfortunately, it may not be applicable to solving

the presented MINLP model because of the poor convergence performance. Even though various initial binary solutions were tested, the convergence still did not perform well.

Penalty Coefficient Methods and Pseudo-integer Method

To solve the resulting NLP problems by EPC, PPC, and PI methods, LINGO uses the generalized reduced gradient (GRG) algorithm. GRG is a gradient-based algorithm that is frequently used to solve large-scale nonlinear programming problems. Details of the GRG method can be seen in Lasdon and Waren (1978), and Drud (1994).

In the NLP model from EPC method, there are 336 continuous variables, 108 linear constraints, and 276 nonlinear constraints. The number of nonlinear constraints is over 70% of total constraints. The u value used herein is 10^6.

The number of variables and constraints of PPC method is the same with EPC method. The p value used herein is 10^{-6}.

In the NLP model from PI method, there are 408 continuous variables, 216 linear constraints, and 240 nonlinear constraints. The number of nonlinear constraints is over 50% of total constraints.

Solving the resulting NLP problems, the objective function value of EPC, PPC, and PI are –219.9, -220.0, and –264.0, respectively. The results show that EPC and PPC have similar objective function value. In addition, PI performs better than EPC and PPC. Using these three methods to transform the original MINLP problem into three continuous NLP problems can eliminate the searching procedure in the discontinuous

domain. However, in the nonlinear constraints of the resulting NLP problems, the multiplication terms in which the division or exponential forms are involved cause a high level of nonlinearity. In other words, it is possible that numerous local optimum exist in the search domain. Consequently, it is very difficult to obtain the global optimum for the resulting NLP problems by traditional gradient-based algorithms.

Since the task is to obtain new rule curves and hedging rules, the objective function values of these three models are preferred over the objective value of the current rule curves and hedging rules, which is –266.0. Unfortunately, the results of these methods did not improve the objective function. The reasons may include that too many local optimums exist or that the initial guess is not well selected. Thus the solution is easily trapped in a local optimum.

Simulated Annealing

Two kinds of hybrid SAs are proposed to solve the original MINLP model for this simplified system and to provide a comparison of the results.

The first approach, HSA1, the binary variables (discontinuous variables) are chosen as the complicating variables evaluated by SA. With given binary variable solution, the resulting model becomes an LP problem. Thus solving the original MINLP problem becomes solving a number of linear programming problems with their corresponding binary variable solutions. In each LP problem of HSA1, there are 336

variables and 360 constraints. The SA control parameters used in this case are: $T_0 = 80$, $N_T = 20$, and $R_T = 0.5$.

The second approach, HSA2, the rule curves and rationing factors (continuous variables) are chose as the complicating variables evaluated by SA. With the given rule curves and rationing factors solution, the resulting model becomes an MILP problem. Thus solving the original MINLP problem becomes a matter of solving a number of MILP problems with their corresponding rule curves and rationing factors solutions. Solving the MINLP model by HSA2, there are 48 rule curves values and 4 rationing factors which need to be evaluated. In each MILP problem of HSA2, there are 356 continuous variables, 66 integer variables, and 384 constraints. The SA control parameters used in this case are: $T_0 = 80$, $N_T = 20$, and $R_T = 0.5$.

Figure 5-4 shows the relationship of objective function value and the number of evaluations in HSA1 and HSA2 approach. The relationship represents the best objective function value found so far after a number of iterations. A comparison of HSA1 and HSA2 in solving the MINLP problems for this simplified system reveals the following:

1. Because HSA1 and HSA2 are iteration approaches, a myriad of LP problems are solved in HSA1 and a myriad of MILP problems are solved in HSA2 to obtain the optimal solution.
2. The numbers of the decision variables and constraints of HSA2 are larger than HSA1. In addition, the binary variables are involved in the resulting MILP model in HSA2. Therefore, the computer solving time of HSA2 in each iteration is longer than that of HSA1.

3. In HSA1, infeasibility may occur. This kind of solution is omitted in SA evaluation.
4. The objective function value of HSA1 is –281.0 and that of HSA2 is –279.1. HSA1 and HSA2 can obtain similar objective function values.

<u>Transformation</u>

Using the transformation technique, there are 650 continuous variables, 66 binary variables, and 1032 linear constraints in the resulting MILP model. The MILP model is then solved by LINO to obtain a new set of rule curves and hedging rules. The objective function value obtained is –281.0, which is superior to the objective function value under the current rule curves and hedging rules. Consequently, the results suggest that the operation for this simplified system can reach better performance if the new rule curves and hedging rules are implemented.

<u>Overall Discussion</u>

To reevaluate the rule curves and hedging rules of the hypothetical simplified system, the above-mentioned methodologies are applied to solve the MINLP model and the results are analyzed and discussed above. The characteristics of these methods are summarized in Table 5-3.

In these methodologies, the MINLP model solved by transformation technique can obtain the most encouraging objective function value. In other words, compared with

other methodologies, the transformation technique is more suitable for solving the MINLP model to reevaluate the current rule curves and hedging rules. The optimal results by the transformation technique are shown in Table 5-4. The new reservoir rule curves and hedging rules are shown in Table 5-5 and Table 5-6.

Examining the optimal rule curve and rationing factor results, it is obvious that most of the values reach either the lower bounds or the upper bounds. This situation implies that there is potential to obtain a better objective function value if the search range becomes larger. However, with a larger search range, the new rule curves are likely to have oscillation distributions and be difficult to follow for real operation.

To discover how the objective function responds on the search range, the sensitivity analysis is implemented by adding four more search range sets and the results are compared with the original setting (Table 5-7). The results of these five scenarios are shown in Table 5-8 and Figures 5-5~5-9. Note that the result of α_1 for RE2 in each scenario can be ignored. The reason is because the model results show that the reservoir storage of RE2 at each time period is either in zone 2 or zone 3, not in zone 1. Therefore, the model just assigns any value, which is either the lower bound or upper bound, as the solution of α_1.

The sensitivity analysis on the search ranges can provide water use and reservoir storage information for decision makers to decide new operating policies. The new rule curves and rationing factors should not only be able to improve the system performance, but also be easy to follow so that the reservoirs can be operated without difficulty.

For example, compare scenario 1 and 3, which have the same search range of rationing factors, the combination of new rule curves and rationing factors in scenario 3 has a better objective function value, even though α_2 for RE1 of scenario 3 is smaller than that of scenario1. It implies that the water use in scenario 3 may be smoother than scenario 1.

The following is another example. Compare scenario 1 and 4, under the same rule curve search ranges, the objective function value of scenario 4 is better than that of scenario 1. For RE1 in scenario 4, it is easier to follow the hedging rules with the same α_1 and α_2 value. Note that since the performance of sensitivity analysis responds to the input data and initial conditions, it is difficult to establish relationships among these variables.

In literature, it is generally difficult to deal with a MINLP problem. Fortunately, in this study, the transformation technique presented herein can take advantage of the special nonlinear formulation structure and convert the proposed MINLP model into a MILP model, which is easier to resolve by standard integer programming algorithms. However, if there is no such transformation technique existing, according to the analysis on other solution methodologies, the proposed hybrid SA may be suitable to handle the original MINLP model, even though the hybrid SA requires numerous evaluations and the computer time is much longer than for other methods.

Table 5-1 Upper Bounds and Lower Bounds Used When Searching for New Rule Curves for Simplified System

Time	RE1				RE2			
	Firm Curve		Target Curve		Firm Curve		Target Curve	
	LB	UB	LB	UB	LB	UB	LB	UB
1	28	32	48	50	18	22	28	30
2	25	29	45	49	15	19	25	29
3	22	26	42	46	12	16	22	26
4	19	23	39	43	9	13	19	23
5	16	20	36	40	6	10	16	20
6	13	17	33	37	3	7	13	17
7	13	17	33	37	3	7	13	17
8	16	20	36	40	6	10	16	20
9	19	23	39	43	9	13	19	23
10	22	26	42	46	12	16	22	26
11	25	29	45	49	15	19	25	29
12	28	32	48	50	18	22	28	30

Table 5-2 Upper Bounds and Lower Bounds Used When Searching for New Rationing Factors for Simplified System

Rationing Factor	RE1		RE2	
	LB	UB	LB	UB
α_1	0.4	0.6	0.5	0.7
α_2	0.6	0.8	0.7	0.9

Table 5-3 Comparison of GBD, PC, PI, SA, and Transformation Technique on Solving MINLP Model for Simplified System

Model Characteristics		GBD		PC		PI	SA		Transformation Technique
		PP	RMP	EPC	PPC		HSA1	HSA2	
Iteration Procedure ?		Yes		No	No	No	Yes	Yes	No
Resulting Problem Type		LP	MILP	NLP	NLP	NLP	LP	MILP	MILP
Number of Variables	Continuous Variables	336	1	336	336	408	336	356	650
	Binary Variables	0	66	0	0	0	0	66	66
Number of Constraints	Linear Constraints	360	Varied	108	108	216	360	384	1032
	Nonlinear Constraints	0	0	276	276	240	0	0	0
Computation Time (CPU Seconds)		< 0.01*	Varied*	12.00	19.00	1.00	< 0.01*	0.01*	8.00
Objective Function Value		N/A		-219.9	-220.0	-264.0	-281.0	-279.1	-281.0

Note: All the model runs are on a PC with 1GHz Pentium III Processor and 1 GB RAM.
* : CPU time per calculation.

Table 5-4 The Optimization Results of MINLP Model Solved by Transformation Technique for the Simplified System

Time	Water Supply			Reservoir Beginning Storage			
	DD1	DD2		RE1		RE2	
		DD2[1]	DD2[2]	Storage	Zone	Storage	Zone
1	8	8	9	35	2	25	2
2	8	8	9	29	2	24	2
3	8	8	10	23	2	23	3
4	6	6	9	17	1	20	2
5	8	8	10	17	2	22	3
6	8	8	10	13	2	22	3
7	6	6	10	9	1	22	3
8	6	6	10	11	1	24	3
9	6	6	10	13	1	26	3
10	6	6	10	15	1	28	3
11	6	6	10	11	1	28	3
12	6	6	10	7	1	28	3

Table 5-5 The New Rule Curves for the Simplified System

Time	RE1		RE2	
	Firm Curve	Target Curve	Firm Curve	Target Curve
1	30	50	20	30
2	29	45	15	25
3	23	46	12	23
4	23	43	9	21
5	17	40	6	16
6	13	37	3	13
7	13	37	7	13
8	16	40	6	16
9	19	43	9	19
10	22	42	12	22
11	25	45	15	25
12	28	48	18	28

Table 5-6 The New Hedging Rules for the Simplified System

Reservoir Storage	Rationing Factor	
	RE1	RE2
Minimum Storage ≤ S_t < Firm Storage	60%	70%
Firm Storage ≤ S_t < Target Storage	80%	90%
Target Storage ≤ S_t ≤ Maximum Storage	100%	100%

S_t : Beginning storage of RE1 (or RE2) in time period t.

Table 5-7 Scenarios of Sensitivity Analysis on the Search Ranges of Rule Curves and Rationing Factors (Based on the Current Setting)

Scenarios	Rule Curves		Rationing Factors	
	LB (Units)	UB (Units)	LB	UB
1	-2	+2	-0.1	+0.1
2	-3	+3	-0.1	+0.1
3	-4	+4	-0.1	+0.1
4	-2	+2	-0.2	+0.2
5	-2	+2	-0.3	+0.3

Table 5-8 Results of Sensitivity Analysis on Rationing Factors

Scenarios	RE1		RE2		Objective Function
	α_1	α_2	α_1	α_2	
1	0.60	0.80	0.70	0.90	-281.0
2	0.60	0.77	0.50	0.80	-282.4
3	0.60	0.78	0.50	0.90	-284.6
4	0.70	0.70	0.80	1.00	-287.0
5	0.69	0.70	0.30	1.00	-287.0

Figure 5-1 Flowchart of v3-GBD

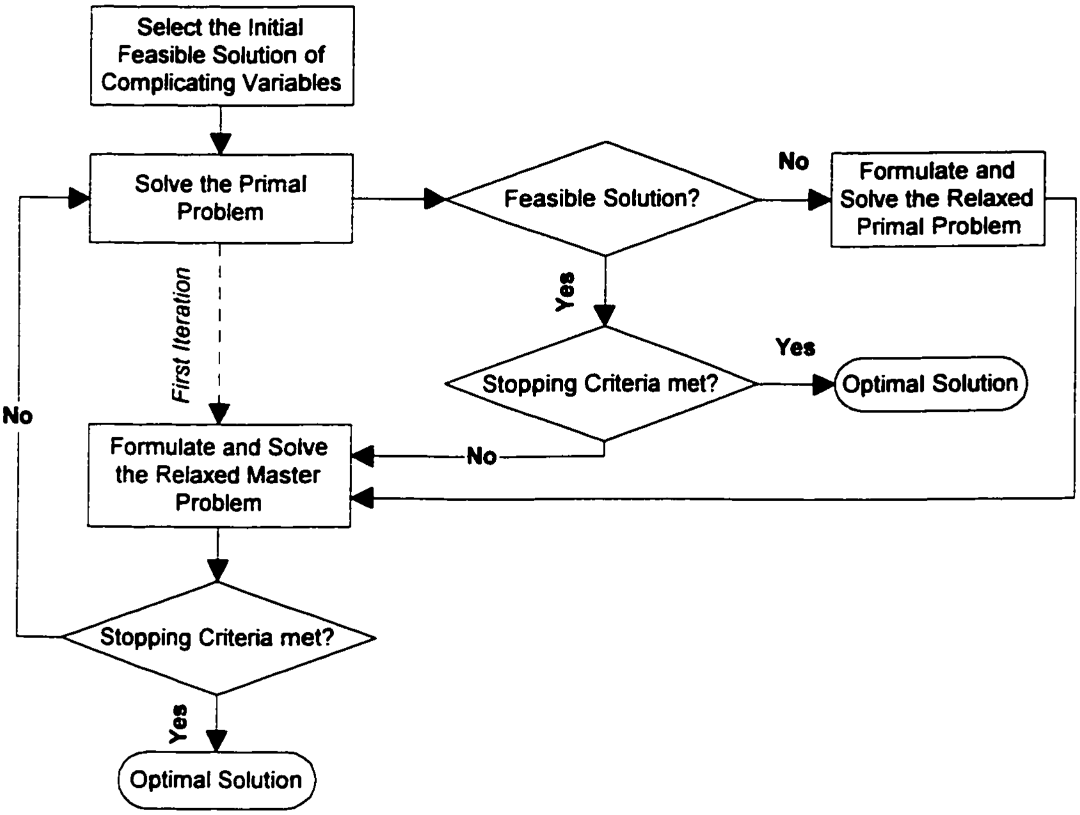


Figure 5-2 The Physical Scheme of Simulated Annealing

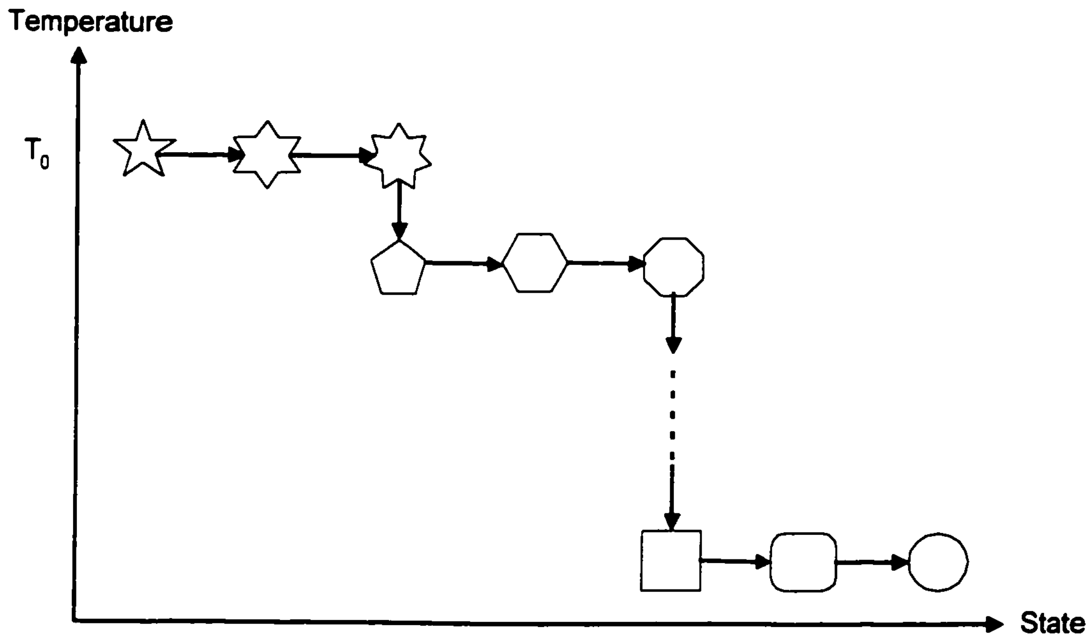


Figure 5-3 The Flowchart of Hybrid Simulated Annealing Approach

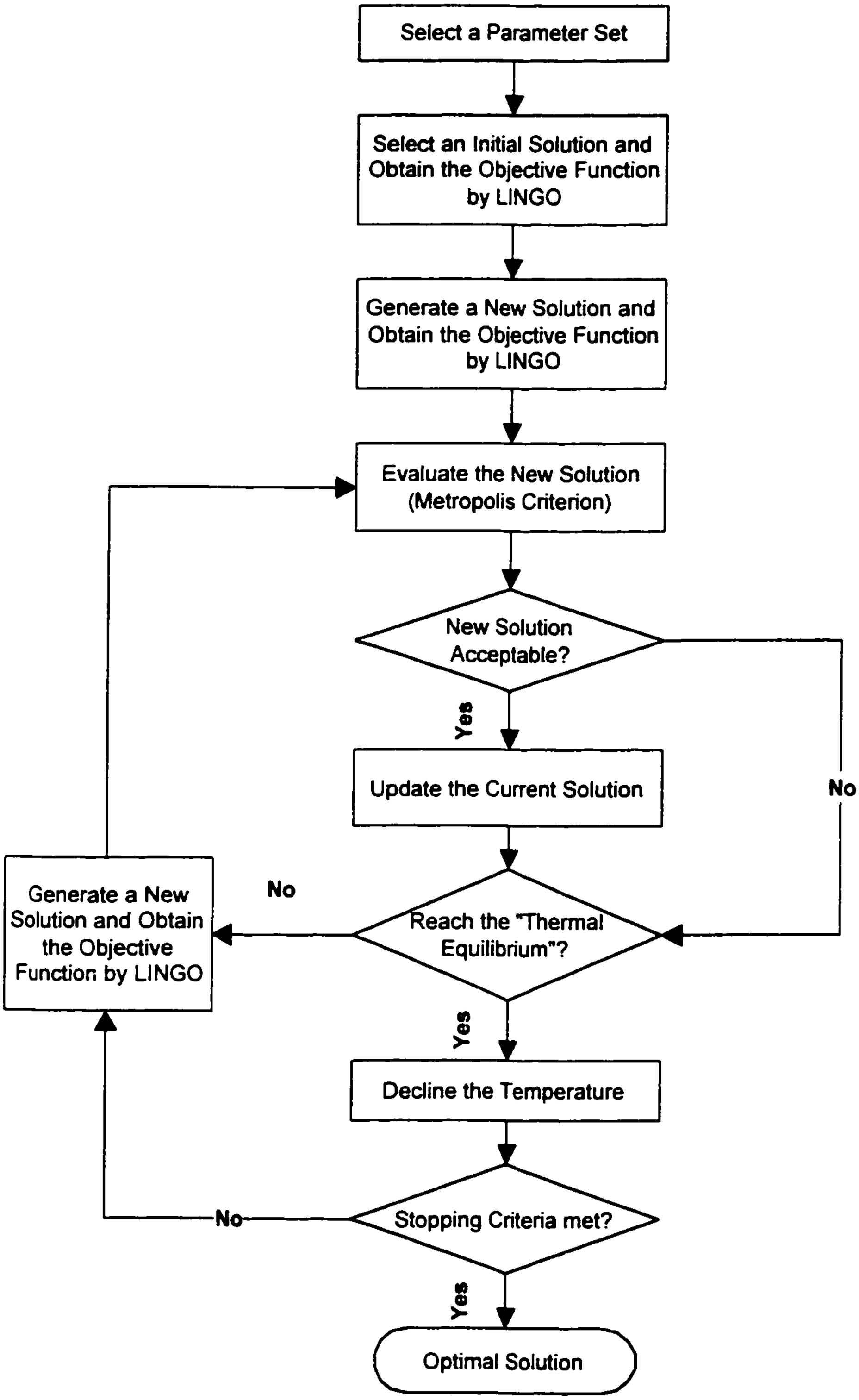
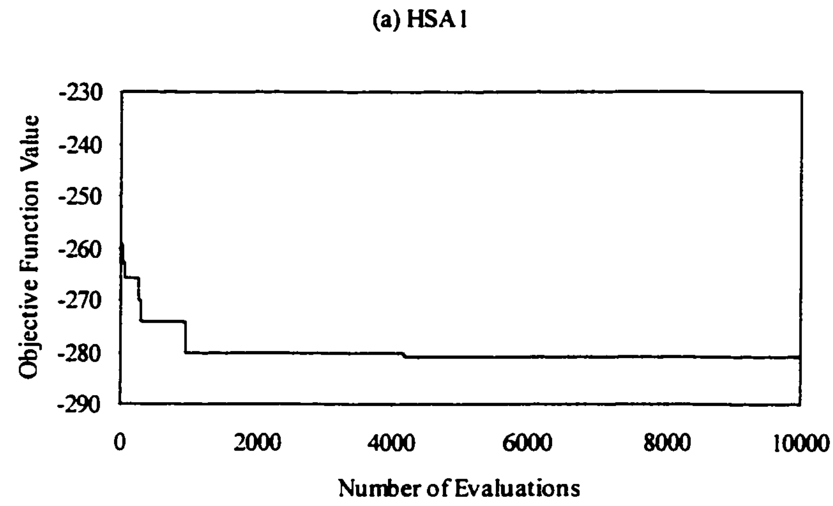


Figure 5-4 Evaluation of Objective Function of HSA1 and HSA2



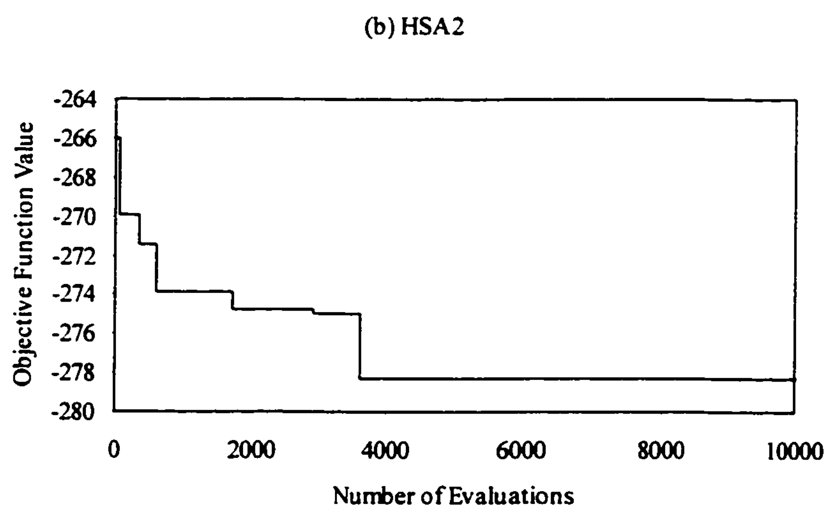
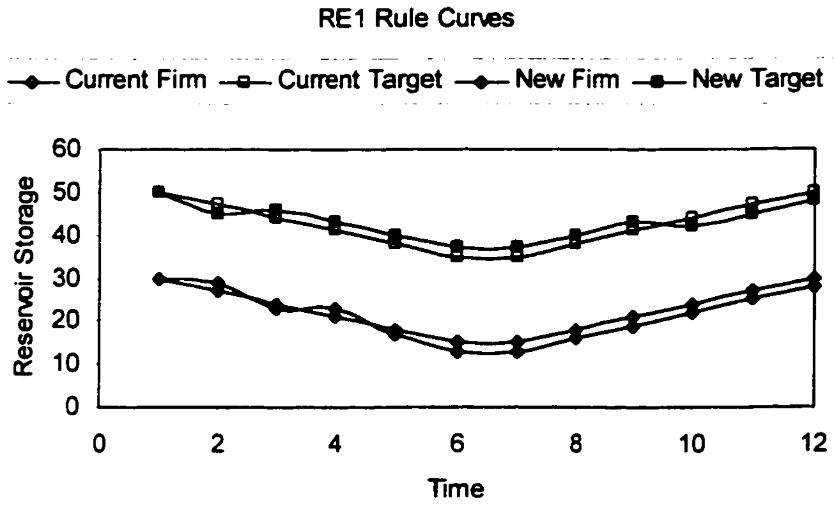


Figure 5-5 The New Rule Curves for the Simplified System (Scenario 1)



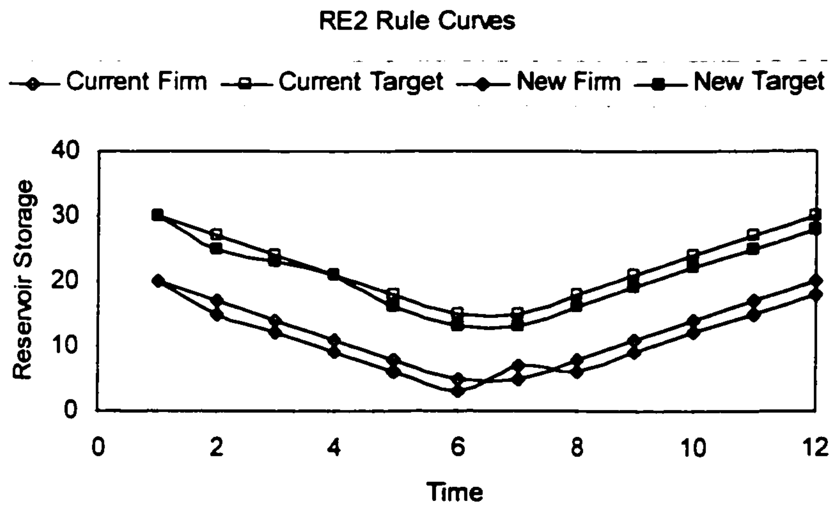
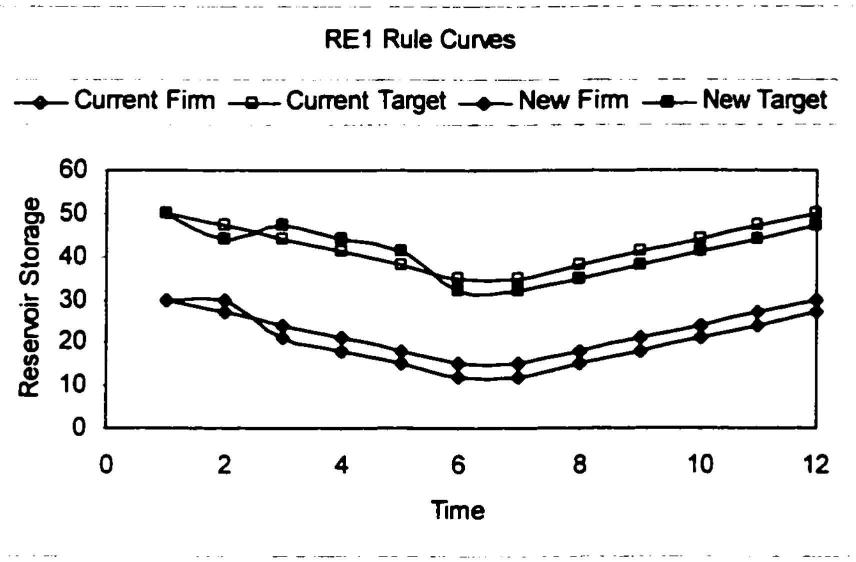


Figure 5-6 The New Rule Curves for the Simplified System (Scenario 2)



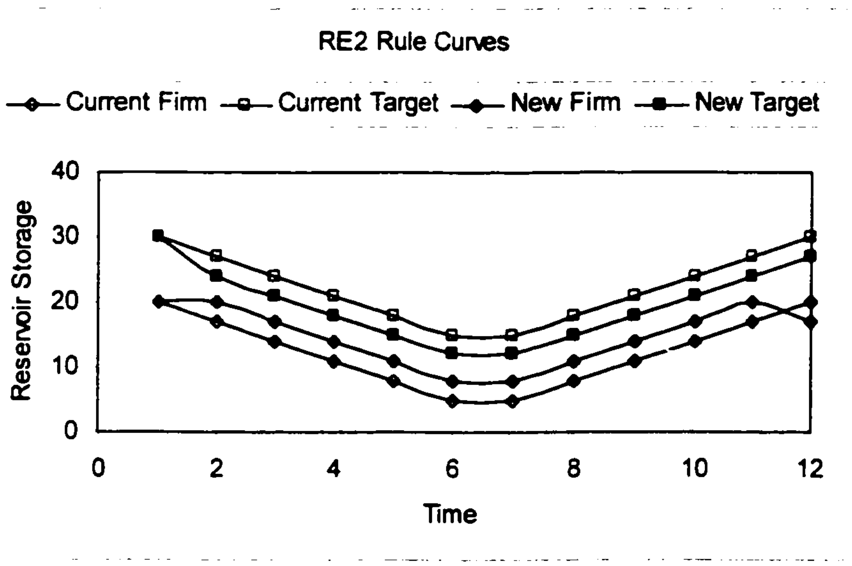
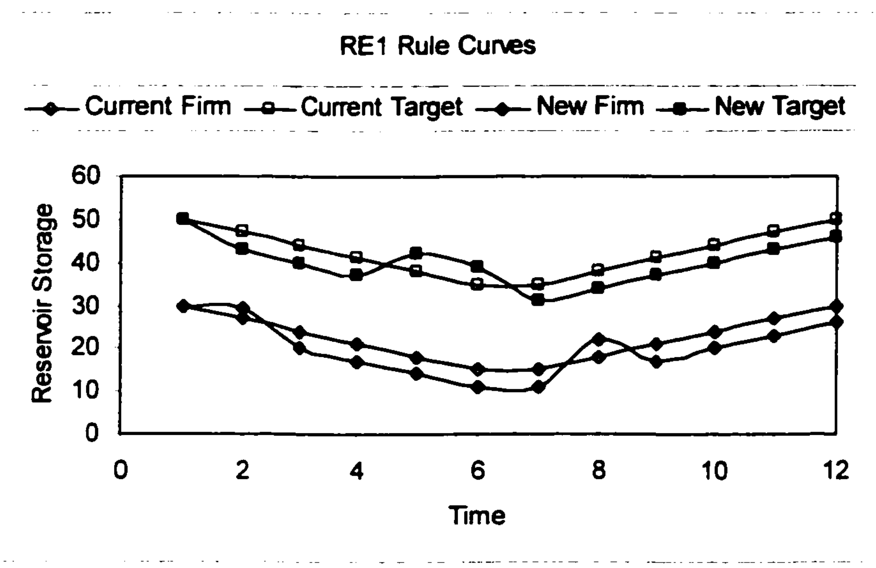


Figure 5-7 The New Rule Curves for the Simplified System (Scenario 3)



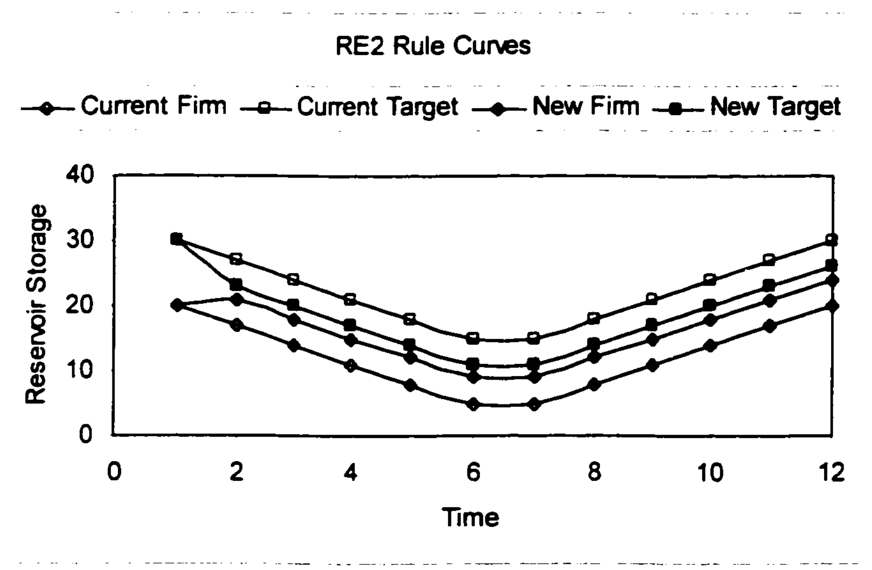
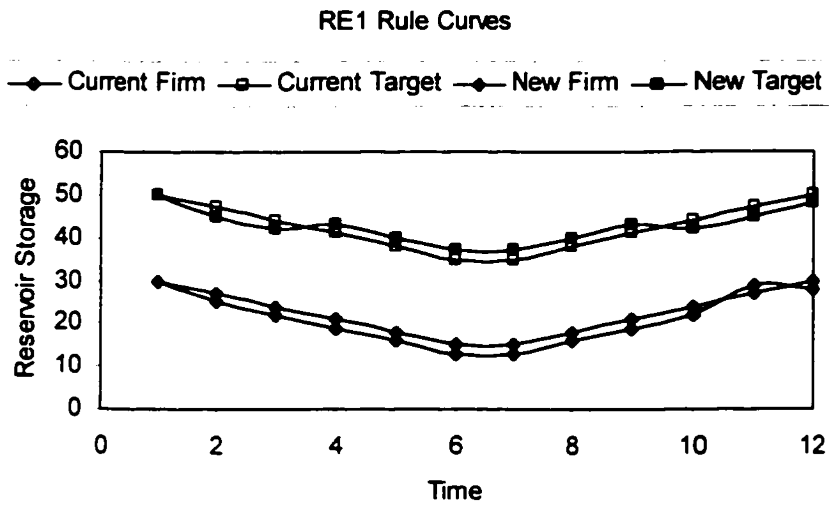


Figure 5-8 The New Rule Curves for the Simplified System (Scenario 4)



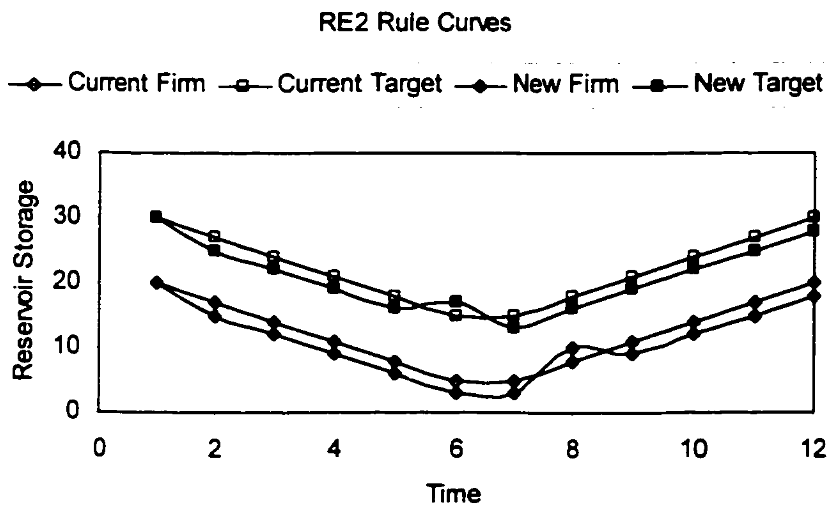
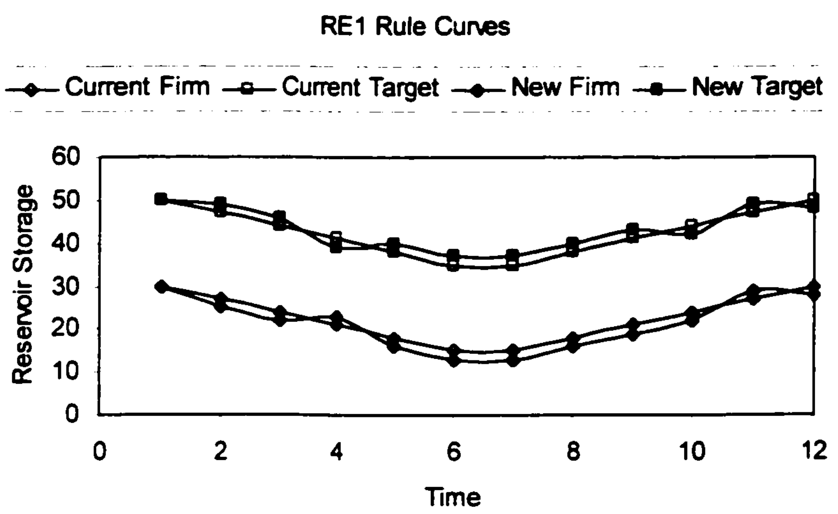
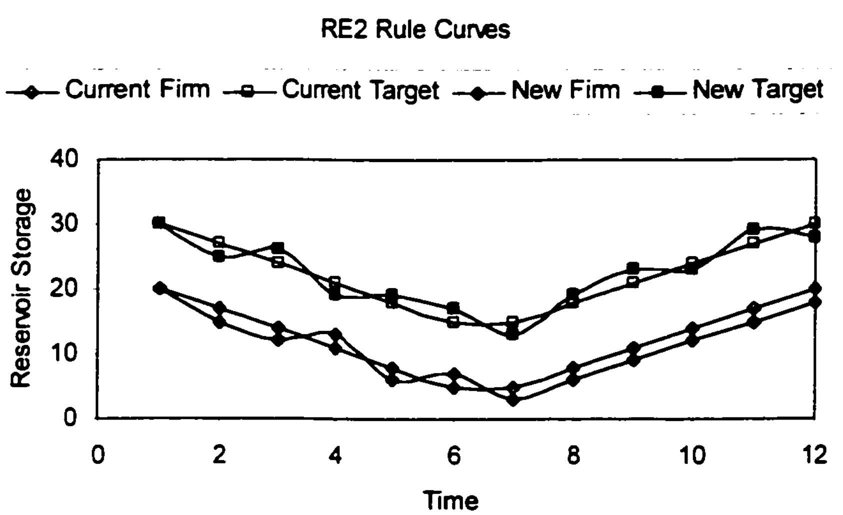


Figure 5-9 The New Rule Curves for the Simplified System (Scenario 5)





CHAPTER 6 CASE STUDY: THE SOUTHERN REGIONAL SYSTEM, TAIWAN

A real-world water distribution system, the southern regional water supply system in Taiwan, will be used as a case study to demonstrate the MILP model presented in Chapter 4 to optimize the system operation with reservoir rule curves and hedging rules. In addition, the MINLP model proposed in Chapter 5 is then used to evaluate and modify the current rule curves and hedging rules in this system. Figure 6-1 shows the geographical area of the region. Figure 6-2 shows layout of the water resources in this region.

6.1 Description of the Southern Regional System

The water distribution system of southern Taiwan covers the following two major river basins: the Tsengwen Basin and the Kaoping Basin. The system supplies water to the Chiayi, Tainan, Kaohsiung, and Pingtung Counties in southern Taiwan. A network representation of the distribution system is shown in Figure 6-3. The three major reservoirs in the Tsengwen Basin are the Tsengwen Reservoir, the Wusantou Reservoir, and the Nanhwa Reservoir. The Tsengwen Reservoir is the largest reservoir in Taiwan, and it is always operated jointly with the Wusantou Reservoir for flood control, and

agricultural, municipal and industrial water supply. Inflow to the Wusantou Reservoir is negligible. Hence, the two reservoirs can be lumped into a single reservoir called the T-W Reservoir. The Nanhwa Reservoir mainly provides municipal and industrial water supply. In the Kaoping Basin, several smaller reservoirs provide municipal and industrial water supply. The basic characteristics of all the reservoirs are shown in Table 6-1. In addition to the reservoirs mentioned, the system has many diversion structures.

In the southern part of Taiwan, almost 90% of the annual rainfall occurs from May to October. As can be seen from Figure 6-4, the distribution of the average annual surface runoff is highly uneven. This creates a challenge to reservoir operators. For example, if a drought occurs and an insufficient amount of water is stored in the reservoirs, future water supply will be in jeopardy. To conserve water and minimize the impact of a severe water shortage in the future, the reservoirs must be operated under the hedging rules.

The network representation in Figure 6-3 shows 14 source nodes, 27 diversion nodes, 21 demand nodes, five reservoir nodes, 13 junction nodes, one low flow requirement node, and 88 links. Reservoir nodes and diversion nodes are the two types of control nodes that control distribution of the water. A diversion node either transfers water to or from another basin, or it supplies demand. Undiverted water is discharged to the ocean.

In Taiwan, for planning purposes, the municipal and industrial water demands are usually considered as one kind of demand, called the public demand. Therefore, two kinds of demands, the agricultural and public demands, are considered in this case study.

The T-W Reservoir has three rule curves, and the Nanhwa Reservoir has two rule curves. The rule curves and the hedging rules of the T-W Reservoir and the Nanhwa Reservoir are described below and shown in Tables 6-2~6-4 and Figure 6-5.

The interpretation of the rule curves and of the hedging rules for the T-W Reservoir is as follows:

1. If the sum of the beginning storages of the Tsengwen and Wusantou Reservoirs is greater than that of the target curve, the planned demand at each demand node is met at 100%.
2. If the sum of the beginning storages of the Tsengwen and Wusantou Reservoirs is greater than that of the firm curve and less than that of the target curve, the planned demand for the agricultural use is met at 75%; but the planned demand for public use is met at 100%.
3. If the sum of the beginning storages of the Tsengwen and Wusantou Reservoirs is less than that of the firm curve, the planned demand for agricultural use is met at 50%; but the planned demand for public use is met at 80%. Note that the flood control curve applies only to the Tsengwen Reservoir. In our analysis, flood control reservation is strictly observed.

The interpretation of the rule curves and of the hedging rules for the Nanhwa Reservoir is as follows:

1. If the beginning storage is greater than that of the target curve, the planned demand at each demand node is met at 100%.

2. If the beginning storage is greater than that of the firm curve and less than that of the target curve, the planned demand at each demand node is met at 90%.
3. If the beginning storage is less than that of the firm curve, the planned demand for each demand node is met at 80%.

Examining the network configuration reveals the following: demand nodes D1 and D4 can receive water from the Tsengwen Reservoir; nodes D2, D3, and D5 can receive water from the Wusantou Reservoir; and node D6 can receive water only from the Nanhwa Reservoir. Water supplies to these six demand nodes are required to satisfy the hedging rules in the optimization model. In the current setting, demand nodes D7 and D8 are not subject to the hedging rules. This is because D7 and D8 can receive water from all of the three reservoirs; and, additionally, two inflows (I3 and I4) can also supply water to D7 and D8.

Consistent with the irrigation practices in Taiwan, the time period for reservoir management and operation is 10 days. A month is divided into three time periods, in which the first two time periods always contain 10 days and the last time period varies from 8 to 11 days, depending upon the particular calendar month under consideration. The water year in Taiwan is from November 1 to October 31. A water year invariably has 36 time periods. In this study, the 10-day basis is preferred as the time period, recognizing that certain time periods may not be exactly 10 days. Additional assumptions made in the optimization model include the following: (1) the source of water supply considered is from the surface water; (2) no loss occurs during the flow transshipment; (3) evaporation loss from the reservoir is negligible; (4) return flow is negligible.

In the network representation, the one low flow requirement node, referred to as the low flow node, in the system can be handled by assigning a lower bound for the low flow arc (Figure 6-6(a)). During normal periods of inflow, this constraint is usually satisfied; however, during periods of drought, this constraint may cause infeasibility. To circumvent this, the low flow node is considered as a demand node in the optimization model, and a dummy node associated with the original low flow node is created (Figure 6-6(b)). Accordingly, Figure 6-6(a) is transformed into Figure 6-6(b) with one dummy node and two artificial arcs. Note that the capacity of the arc, AL, in Figure 6-6(a) is also modified as shown in Figure 6-6(b).

In the objective function, the low flow node is specified with a corresponding unit cost. Therefore, the optimization model will "supply" the low flow requirement as much as possible. During normal periods of inflow, there is sufficient water to satisfy the low flow requirement, and all surplus water will flow into the dummy node and then return to the low flow node. The total amount of water that flows into the low flow node is the summation of the low flow requirement and the surplus water. However, during a drought period, if there is a shortage of water to satisfy the low flow requirement, the amount of water that flows into the low flow node will be less than the low flow requirement, but infeasibility is avoided and no water will flow into the dummy node.

6.2 System Optimization with Current Rule Curves and Hedging Rules

The following sections will describe the MILP model for the southern system in Taiwan in order to consider the reservoir rule curves and hedging rules and also to provide a discussion of the numerical results.

6.2.1 MILP Optimization Model

In the MILP model, the following operational objectives are considered herein: (1) maximization of water supply for public demand; (2) maximization of water supply for agricultural demand; (3) satisfaction of the low flow requirement; (4) maximization of reservoir storage. Using the weighting method combines the four objectives to reflect their relative importance.

The most important objective is to distribute the available water and to maximize supply for public demand, or, in other words, to minimize any shortage in public demand. The second most important objective is to maximize the water supply for agricultural demand. The low flow requirement is the third concern. Least important, maximization of the reservoir storage, ensures that there is sufficient amount of water in storage for future water supply and continuing operations. Therefore, the objectives are prioritized in the following descending order: public demand, agricultural demand, low flow requirement, and reservoir storage. The maximization problem is converted to a standard minimum-cost problem by multiplying the objective function with a minus sign.

The one-year MILP model for the southern system in Taiwan can be formulated as follows:

$$Min.\sum_{t=1}^{36}\left\{-\sum_{\substack{j\in \mathbf{N}_P\\(i,j)\in\mathbf{A}}}(C_P)_{j,t}x_{(i,j),t}-\sum_{\substack{j\in \mathbf{N}_A\\(i,j)\in\mathbf{A}}}(C_A)_{j,t}x_{(i,j),t}-\sum_{\substack{j\in \mathbf{N}_L\\(i,j)\in\mathbf{A}}}(C_L)_{j,t}x_{(i,j),t}-\sum_{\substack{j\in \mathbf{N}_R\\(i,j)\in\mathbf{A}_R}}(C_R)_{j,t}x_{(i,j),t}\right\} \quad (6\text{-}1)$$

s.t.

$$x_{(j,i),t} = IN_{j,t} \quad , \quad \forall j \in \mathbf{N}_I \quad (6\text{-}2)$$

$$\sum_{(j,i)\in\mathbf{A}} x_{(j,i),t} - \sum_{(i,j)\in\mathbf{A}} x_{(i,j),t} = 0 \quad , \quad \forall j \in \{\mathbf{N}_G \cup \mathbf{N}_{Drv}\} \quad (6\text{-}3)$$

$$\sum_{(j,i)\in\mathbf{A}} x_{(j,i),t} - \sum_{(i,j)\in\mathbf{A}} x_{(i,j),t} + Y = 0 \quad , \quad \forall j \in \mathbf{N}_R \quad (6\text{-}4)$$

$$Y = x_{(i,j),t+1} - x_{(i,j),t} \quad , \quad \forall (i,j) \in \mathbf{A}_R \quad , \quad \forall j \in \mathbf{N}_R \quad (6\text{-}5)$$

$$\sum_{(i,j)\in\mathbf{A}} x_{(i,j),t} \le LW_{j,t} \quad , \quad \forall j \in \mathbf{N}_L \quad (6\text{-}6)$$

$$x_{(i,j),t} \le D_{j,t} \quad , \quad \forall j \in \{\mathbf{N}_{P2} \cup \mathbf{N}_{A2}\} \quad (6\text{-}7)$$

Eqs. (4-22)~(4-29)

where

$\mathbf{N}_R$ = subset of $\mathbf{N}$ for reservoir nodes;

$\mathbf{N}_I$ = subset of $\mathbf{N}$ for inflow nodes;

$\mathbf{N}_G$ = subset of $\mathbf{N}$ for junction nodes;

$\mathbf{N}_{Drv}$ = subset of $\mathbf{N}$ for diversion nodes;

$\mathbf{N}_L$ = subset of $\mathbf{N}$ for the low flow nodes;

$IN_{j,t}$ = amount of inflow to inflow node j;

$LW_{j,t}$ = low flow requirement at low flow node j;

$\mathbf{N}_p$ = subset of **N** for the public demand nodes;

$\mathbf{N}_{P2}$ = subset of **N** for the public demand nodes not subject to hedging rules;

$\mathbf{N}_A$ = subset of **N** for the agricultural demand nodes;

$\mathbf{N}_{A2}$ = subset of **N** for the agricultural demand nodes not subject to hedging rules;

C_P = unit cost of supply to public demand;

C_A = unit cost of supply to agricultural demand;

C_L = unit cost of flow to the low flow node;

C_R = unit cost of storage arc of the reservoir.

The composite objective function, Eq. (6-1), is a combination of four objectives. Eqs. (6-2)~(6-5) are the continuity equations for inflow, junction, diversion and reservoir nodes (here, $b_{j,t}$ is zero). Eq. (6-6) specifies low flow requirement. Eq. (6-7) specifies the water supply constraints for demand nodes that are not subject to hedging rules. Note that the water supply is assumed to be equal to or less than the planned demand. The effect of this constraint is to avoid a situation under which certain demand nodes may receive a surplus supply and some other demand nodes may experience a severe shortage. Eqs. (4-22)~(4-29) have been defined before. Note that k=1, NK=1, PE^k=1 for D1~D6; $\mathbf{K}_j$={T-W Reservoir} for D1~D5, and $\mathbf{K}_j$={Nanhwa Reservoir} for D6. The weighting factors of these objectives are shown in Table 6-5. The values are obtained from consultations with engineers in Taiwan. In the minimum-cost optimization problem, the weighting factor for the public demand is the smallest to ensure that its priority is the highest. Similarly, the weighting factors of the other three objectives are assigned with values which correspond to their priorities.

6.2.2 Numerical Results and Discussions

In this study, the MILP optimization problem is solved by LINGO. All the input data is provided by the Water Resources Bureau in Taiwan. The inflow data obtained for this study comprises 20 years of data (1974~1993). Figure 6-7 shows the variation of the annual inflows. Table 6-6 shows the annual inflow for each year. The third low inflow, which occurred in 1984 (5569.11 million cubic meters), is selected to test the optimization model.

Note that the demand data for each demand node changes with the time period during the year. There are 36 different planned demands in 36 time periods for each demand node. The demand data for each demand node is shown in Table 6-7. The initial reservoir storage of each reservoir used in the optimization model is the average storage of the first 10-day period of the historical records. The initial storage of Tsengwen, Wusantou, and Nanhwa Reservoirs are 303.60, 45.07, and 110.65 million cubic meters, respectively.

In the 36-time-period optimization model, there are 4,188 decision variables, including 210 integer variables and 3,137 constraints. Because the initial reservoir storage is known, it is not necessary to consider the integer variables for the beginning of the first time period. The input data consists of the inflow, planned demands, water supply limitation, link capacity limitation, and reservoir storage limitation for each time period. The reservoir rule curves and the hedging rules are also part of the input data.

The optimal regional water supply allocation solution has been obtained using LINGO. The results indicate that the reservoir release and water supply satisfy the rule curves and the hedging rules simultaneously. From Table 6-8, it is evident that the optimal solutions of the supply and reservoir storage zones for D1 to D5, the T-W Reservoir, D6, and the Nanhwa Reservoir satisfy the hedging rules. For example, the solution shows that the beginning storage of the T-W Reservoir in the second time step is in zone 2, and the corresponding optimal water supply for the D1 to D5 is in zone 2, not in zone 1 or zone 3.

After testing the optimization model for the drought year, the inflow data of 20 years, including the normal, wet, and dry years, is used to run the optimization model once per year to obtain the optimal solutions of water supply and reservoir storage. For planning purposes, it is not necessary to show the optimal water supply to each demand node and the optimal reservoir storage of each reservoir in each time period of each year. Instead, the average water supply and reservoir storage variations of the entire system for each of the 36 time periods in one year after the 20 runs are evaluated. The purpose of this procedure is to examine the average performance of the optimal operation of this system with hedging rules and various hydraulic situations. It is assumed that the demand of each demand node is the same in each year, but varies with the time period.

Depending on the hydrologic data, the running time for each year varies from 3 seconds to 4495 seconds on a PC with 1GHz Pentium III Processor and 1 GB RAM. The results of average supply and shortage from the 20-optimization runs are shown in Figures 6-8~6-10. In Figure 6-8, the axis represents the 20 different water years with

different inflows, and the ordinate in each figure represents different shortage information. The information presented allows decision makers to evaluate the average water supply and shortage conditions under a long-term operation when the system is operated with the hedging rules. For example, from Figure 6-10, it can be seen that the average shortage is more severe from the second to the eleventh time periods every year, which implies that the probability of water shortage during these periods may be higher than at other periods; and the water supply from other sources or a compromise between different demands may be needed in advance to avoid a shortage.

Table 6-9 shows the sensitivity analysis results of total water supply and shortage to rationing factors. The values in the table are the averages of 20 runs. The relationship between the water supply and rationing factors can be explored via this table. For example, considering demand nodes D1~D4, the water supply of case 2-1 (rationing factors of the T-W Reservoir reduced by 0.1) is similar to that of case 3-1 (rationing factors of the T-W Reservoir increased by 0.1). As to D5, in which the planned demand is larger, the water supply of case 2-1 is less than that of case 3-1. Meanwhile, examining the results of D6, which is directly affected by the operation of the Nanhwa Reservoir, there is no major difference in water supply between case 2-1 and case 3-1. The results show that the rationing factors of the T-W Reservoir are not sensitive to D1~D4 and D6, but sensitive to D5.

The following is another example. For D6, the water supply of case 2-2 (rationing factors of the Nanhwa Reservoir reduced by 0.1) is less than that of case 3-2 (rationing factors of the Nanhwa Reservoir increased by 0.1). Meanwhile, for D1~ D4, the water

supply of case 2-2 is similar to that of case 3-2; however, for D5, the water supply of case 2-2 is less than that of case 3-2. The results show that the rationing factors of the Nanhwa Reservoir are not sensitive to D1~D4, but sensitive to D5 and D6. Since sensitivity analysis is predicated on input data and a given set of base and initial conditions, it is difficult to establish relationships among the variables. But, it is interesting to note that most of the water supply results from case 1-1 to case 3-2 are superior to that of case 0, which uses the original set of rationing factors. This implies that, the current hedging rules should be modified to improve system operation.

In this study, for demand nodes, D7 and D8, the sources are I3, I4, the T-W Reservoir, and the Nanhwa Reservoir. To maximize the water supply to D7 and D8, the optimization model will first allocate water from I3 and I4. If this amount of water is insufficient to meet the planned demands, the optimization model will then release the water from the reservoirs to supply D7 and D8 to minimize the objective function, because D7 and D8 are public demand nodes and have the highest priorities.

It is important to note that after examining the water supply results, the demand nodes in this system can be approximately divided into two parts: D1~D8 which have more water shortage, and D9~D21 which have less water shortage. This is mainly because the inflow that can supply D9~D21 is more plentiful than that for D1~D8. Consequently, system managers may consider the feasibility of inter-basin water supply to supplement the water delivery to D1~D8.

6.3 Evaluation of Rule Curves and Hedging Rules

In the southern system in Taiwan, the recent population and economic growth have caused increasing demands in water supply. In addition, the sediments dramatically have changed the volumes of the reservoirs since they were constructed. For instance, up to this point, the Wusantou Reservoir has already lost approximately 40% of its original volume. Therefore, to improve the performance of system operation, it is necessary to modify the current reservoir rule curves and hedging rules, which were determined beforehand in the planning stage and may not be suitable to the current situation.

In this system, Tsengwen Reservoir is the only reservoir, which has the flood control function. The purpose of the reservoir flood control curve is to provide a storage space to store the water when a flood occurs and to reduce the downstream flooding damage. Analyzing the flood control function of a reservoir requires specific hydraulic aspects and a smaller time scale. Because this study focuses on the system optimization for planning purposes, modifying the flood control curve of the Tsengwen Reservoir is not included here. Consequently, there are four rule curves that need to be modified: the firm storage and target storage curves of T-W Reservoir, and the firm storage and target storage curves of Nanhwa Reservoir. In addition, the six rationing factors are modified as well in this case study. Based on the analysis on the MINLP model in Chapter 5, the transformation technique is chosen to solve the MINLP model for this system.

6.3.1 MINLP Optimization Model

The formulation of the one-year MINLP model for the southern system in Taiwan is similar to the MILP model presented earlier, but the rule curves and rationing factors are unknown here. To compare the performances of new and current rule curves and hedging rules, the hydraulic characteristics of 1984 are chosen as an illustrative example.

To avoid obtaining a new set of rule curves with randomly oscillatory distribution, a set of lower bounds and upper bounds for rules curves are assumed. The range assumption is also applied to search for new rationing factors which will eliminate any possibility of a large difference between the new α_1 and α_2.

For the T-W Reservoir, the lower bounds and the upper bounds of the firm storage and target storage are assumed to be the original values minus and plus 50 million cubic meters. The allowed minimum value for the firm storage curve is assumed as 20 million cubic meters. If the assumed lower bound of target storage is less than the upper bound of firm storage, these two values are substituted by each other. The lower bounds and the upper bounds of rationing factors for the agricultural demands are assumed as the original values minus and plus 0.1. The rationing factors for the public demands are arbitrarily assigned without significant difference. The assumed lower bounds and upper bounds of rule curves and rationing factors are shown in Table 6-10 and 6-11.

For the Nanhwa Reservoir, the lower bounds and the upper bounds of the firm storage and target storage are assumed to be the original values minus or plus 10 million cubic meters. The allowed minimum value for the firm storage curve is assumed as 2

million cubic meters. If the assumed lower bound of target storage is less than the upper bound of firm storage, these two values are substituted by each other. The lower bounds and the upper bounds of rationing factors are assumed to be the original values minus and plus 0.05. The assumed lower bounds and upper bounds of rule curves and rationing factors are shown in Table 6-10 and 6-11.

Note that the initial storage of each reservoir is known beforehand. Unlike the MILP model above, the rule curves are unknown. Also, it is not certain which storage zone the initial reservoir storage belongs to in the beginning. Therefore, the integer variables for the initial stage may be considered in the MINLP model. In this case, after examining the initial storage, lower bound, and upper bound of rule curves in the beginning of the first time period for the Tsengwen, Wusantou, and Nanhwa Reservoirs, it is found that the integer variables for the T-W Reservoir need be considered. The integer variables for Nanhwa Reservoir in the beginning are ignored because the initial storage of Nanhwa is certainly in zone 2.

6.3.2 Numerical Results and Discussions

Using the transformation technique, there are 5912 continuous variables, 216 integer variables, and 6378 constraints in the resulting MILP model. A new set of rule curves and hedging rules can be obtained by solving this model. The resulting objective function value is −1370634, which is superior to the original objective function value, −1331513, under current rule curves and hedging rules. The comparison of system

operation between the current and new rule curves and hedging rules are shown in Table 6-12. This result demonstrates that the system can improve the performance of reservoir operation if the resulting new rule curves and hedging rules are incorporated in the system operation.

In general, one reservoir has only one set of rule curves and hedging rules for long-term operation. However, this set of rule curves and hedging rules may not suit drought periods. Therefore, determining the rule curves and hedging rules for reservoir operation in dry years and normal years are of interest in this study.

To determine the rule curves and hedging rules for dry years, it is necessary to select a set of hydraulic years to represent the situation in dry years. In this study, the five years with the lowest total annual inflows in the historical records are chosen to represent the dry years. These representative years are: 1980, 1993, 1984, 1991, and 1986.

The one-year basis MINLP model is then implemented to obtain the new rule curves and hedging rules for each year. After five model runs, five sets of rule curves and hedging rules are achieved. In each set, there may be a number of curve oscillations which occur. The final rule curves and hedging rules for dry year operation are determined by averaging the value at each time period of each rule curve. Thus the curves can be smoother and easier to follow. The final rationing factors are similarly determined by averaging the five sets of rationing factors. The suggested rule curves and rationing factors for dry year operation are shown in Figure 6-11 and Tables 6-13 ~ 6-15.

When the system is operated with the current rule curves and hedging rules, the optimization results show that the average annual water shortage in these five dry years is

697.76 million cubic meters. If the system is operated with the suggested rule curves and hedging rules, the optimization results show that the average annual water shortage in these five dry years is 650.58 million cubic meters. Examining these two situations, it is evident that the suggested rule curves and hedging rules for dry year operation can improve the system operation.

Similarly, the sixth to fifteenth years in the twenty historical records sorted in ascending order are chosen to represent the normal years. These years are: 1988, 1987, 1989, 1983, 1979, 1985, 1982, 1978, 1992, and 1976. After ten model runs, the final rule curves and rationing factors are determined by averaging these ten model results. The rule curves and rationing factors for normal year operation are shown in Figure 6-12 and Table 6-16 ~ 6-18.

When the system is operated with the current rule curves and hedging rules, the optimization results show that the average annual water shortage in these ten normal years is 434.90 million cubic meters. If the system is operated with the suggested rule curves and hedging rules, the optimization results show that the average annual water shortage in these ten normal years is 375.26 million cubic meters. Examining these two situations, it is evident that the suggested rule curves and hedging rules for normal year operation can improve the system operation.

The result of a comparison between these two sets of rule curves and hedging rules for the T-W Reservoir shows that the target curve for dry year operation is generally higher than that for normal year operation; and the firm curve for dry year operation is generally lower than that for normal year operation. It implies that the model prefers to

let the hedging be active for dry year operation earlier than that for normal year operation, thus saving the water for future use. Because the water in a dry year is saved earlier than during a normal year, the firm curve of dry year operation can be lower than that of normal year operation. A similar situation also applies to the Nanhwa Reservoir but the target curve of dry year operation is closer to that of a normal year.

The average annual water shortage under the current and suggested rule curves and hedging rules for dry and normal year operation are summarized in Table 6-19.

In summary, the current rule curves and hedging rules can be modified via the proposed MINLP model to improve the current system operation. The results obtained can provide information which includes the reservoir operation and water usage in the system so that decision makers can decide optimal operating policies for planning purposes.

Table 6-1 Reservoir Characteristics, Southern Regional System, Taiwan

Reservoir	Active Storage (Million Cubic Meters)	Main Purposes
Tsengwen	692.69	F, A, I, M, P
Wusantou	83.76	
Nanhwa	149.46	I, M
Chengchinghwu	5.00	A,I, M
Fengshan	8.30	I, M

F : Flood Control

A : Agricultural Water Supply

I : Industrial Water Supply

M : Municipal Water Supply

P : Hydropower

Table 6-2 Rule Curves of the T-W Reservoir and Nanhwa Reservoir

Units: Million Cubic Meters

Time	T-W			Nanhwa	
	Firm Curve	Target Curve	Flood Control Curve	Firm Curve	Target Curve
1	240.0	360.0	500.0	96.4	122.4
2	230.0	350.0	480.0	92.4	111.4
3	220.0	330.0	460.0	82.4	104.8
4	210.0	310.0	440.0	77.8	96.4
5	200.0	280.0	420.0	73.2	88.4
6	190.0	250.0	400.0	60.9	84.4
7	170.0	220.0	380.0	57.9	80.4
8	160.0	190.0	360.0	48.9	71.4
9	150.0	175.0	340.0	46.1	66.0
10	120.0	145.0	320.0	35.7	54.9
11	90.0	115.0	300.0	29.1	47.4
12	80.0	100.0	280.0	22.5	40.9
13	55.0	80.0	260.0	13.3	32.2
14	40.0	65.0	240.0	4.0	23.4
15	30.0	50.0	220.0	2.8	18.0
16	30.0	40.0	220.0	2.8	27.8
17	30.0	50.0	220.0	32.2	96.4
18	40.0	70.0	230.0	50.4	149.5
19	60.0	90.0	250.0	67.8	149.5
20	80.0	120.0	300.0	64.2	149.5
21	105.0	150.0	360.0	69.6	149.5
22	130.0	180.0	420.0	86.4	149.5
23	155.0	210.0	460.0	133.9	149.5
24	180.0	240.0	581.0	143.1	149.5
25	200.0	270.0	617.0	143.1	149.5
26	240.0	300.0	617.0	143.1	149.5
27	280.0	330.0	617.0	140.8	149.5
28	280.0	360.0	617.0	140.8	149.5
29	280.0	360.0	617.0	138.5	149.5
30	280.0	360.0	617.0	136.2	149.5
31	280.0	360.0	617.0	134.4	143.8
32	280.0	360.0	580.0	131.6	142.2
33	280.0	360.0	570.0	122.4	140.6
34	280.0	360.0	560.0	118.0	131.6
35	260.0	360.0	540.0	113.6	129.3
36	250.0	360.0	520.0	104.8	127.0

Table 6-3 Hedging Rules of the T-W Reservoir

Reservoir Storage	Rationing Factor	
	Agricultural Demand	Public Demand
Minimum Storage ≤ $S_{T,t} + S_{W,t}$ < Firm Storage	50%	80%
Firm Storage ≤ $S_{T,t} + S_{W,t}$ < Target Storage	75%	100%
Target Storage ≤ $S_{T,t} + S_{W,t}$	100%	100%

$S_{T,t}$: Beginning storage of the Tsengwen Reservoir in time period t.
$S_{W,t}$: Beginning storage of the Wusantou Reservoir in time period t.

Table 6-4 Hedging Rules of the Nanhwa Reservoir

Reservoir Storage	Rationing Factor
Minimum Storage ≤ $S_{N,t}$ < Firm Storage	80%
Firm Storage ≤ $S_{N,t}$ < Target Storage	90%
Target Storage ≤ $S_{N,t}$	100%

$S_{N,t}$: Beginning storage of the Nanhwa Reservoir in time period t.

Table 6-5 Weighting Factors Used for Southern Regional System, Taiwan

Priority	Objectives	Order of Magnitude	Weighting Factor
1	Supply for the Public Demands	10^{-1}~10^{1}	1.0E+3
2	Supply for the Agricultural Demands	10^{-2}~10^{1}	1
3	The Low Flow Requirement	10^{-1}~10^{0}	1.0E-3
4	Reservoir Storage	10^{-1}~10^{2}	1.0E-6

Table 6-6 Annual Inflows, 1974~1993 (Sorted in Ascending Order)

Year	Annual Inflow (Million Cubic Meters)
1980	2840.80
1993	4082.37
1984	5569.11
1991	6525.27
1986	6877.09
1988	7068.27
1987	7228.66
1989	7444.10
1983	7454.69
1979	7873.59
1985	8189.84
1982	8591.37
1978	8615.88
1992	8984.99
1976	10015.27
1974	10562.96
1981	10599.54
1975	11051.27
1990	11583.94
1977	13316.01

Table 6-7 Demand Data

Units: Cubic Meters Per Second

Time	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
1	5.77	2.93	1.21	0.01	1.05	9.45	0.47	2.12	2.23	2.33	3.82
2	5.77	2.93	1.21	0.02	1.05	9.45	0.47	2.12	2.85	3.22	5.20
3	5.77	2.93	1.21	0.05	0.29	9.45	0.47	2.12	3.80	3.87	5.57
4	5.74	3.11	1.21	0.07	26.25	9.31	0.47	2.56	3.03	3.35	4.63
5	5.74	3.05	1.55	0.08	22.74	9.31	0.47	2.56	3.70	4.70	4.03
6	5.74	3.05	1.55	0.12	7.24	9.51	0.48	2.12	3.67	3.87	3.17
7	5.68	3.05	1.36	0.10	2.16	9.51	0.48	2.12	4.01	5.11	3.67
8	5.68	2.93	1.36	0.09	8.82	9.51	0.48	2.12	4.13	4.73	4.04
9	5.68	2.93	1.36	0.08	18.64	9.51	0.48	2.12	4.80	5.12	7.95
10	5.88	2.93	1.36	0.09	17.15	9.51	0.48	2.12	6.36	6.46	6.07
11	5.88	2.93	1.36	0.05	12.74	9.45	0.47	2.12	4.43	4.33	6.23
12	5.88	2.93	1.36	0.01	1.05	9.45	0.47	2.58	1.43	1.43	5.59
13	5.75	3.05	1.36	0.00	16.84	9.45	0.47	2.58	1.52	1.52	8.37
14	5.75	3.05	1.21	0.00	17.55	9.45	0.47	2.58	0.30	1.30	7.77
15	5.75	3.05	1.21	0.00	20.90	9.51	0.48	2.58	0.00	0.00	3.39
16	5.78	3.05	1.21	0.00	6.41	9.31	0.47	2.58	0.00	0.00	5.50
17	5.78	2.98	1.21	0.00	10.28	9.31	0.47	2.58	0.10	0.00	8.86
18	5.78	2.98	1.21	0.00	21.58	9.31	0.47	2.18	0.70	0.95	6.90
19	5.80	2.98	1.21	0.01	27.69	9.31	0.47	2.18	0.71	0.75	6.11
20	5.80	3.05	1.21	0.00	39.13	9.31	0.47	2.33	0.96	1.56	7.11
21	5.80	3.05	1.21	0.01	61.68	9.45	0.47	2.33	3.74	3.99	7.84
22	5.65	3.05	1.36	0.00	26.19	9.45	0.47	2.33	0.42	0.42	6.61
23	5.65	3.11	1.36	0.00	41.92	9.45	0.47	2.33	0.39	0.39	7.08
24	5.65	3.11	1.36	0.00	46.02	9.45	0.47	2.58	0.53	0.53	9.50
25	5.47	3.11	1.36	0.00	41.09	9.41	0.47	2.58	0.72	0.72	7.90
26	5.47	3.11	1.36	0.02	26.91	9.41	0.47	2.12	1.02	1.52	7.38
27	5.47	3.05	1.36	0.00	28.92	9.41	0.47	2.12	1.41	1.67	5.42
28	5.27	3.05	1.36	0.05	34.63	9.41	0.47	2.12	1.70	1.79	0.05
29	5.27	3.05	1.36	0.06	17.82	9.41	0.47	2.12	1.94	2.94	0.35
30	5.27	2.98	1.36	0.04	9.48	9.51	0.48	2.12	0.59	0.59	0.31
31	5.55	2.98	1.36	0.06	0.97	9.51	0.48	2.12	1.51	1.79	0.39
32	5.55	2.98	1.36	0.07	0.97	9.51	0.48	2.12	1.68	1.68	0.52
33	5.55	3.05	1.36	0.08	0.97	9.51	0.48	2.12	1.73	1.95	0.14
34	5.47	3.05	1.36	0.10	0.97	9.51	0.48	2.12	1.63	1.63	0.60
35	5.47	3.05	1.36	0.09	0.97	9.51	0.48	2.12	1.80	1.77	0.84
36	5.47	3.05	1.36	0.08	1.06	9.51	0.48	2.12	1.52	1.72	0.60

Table 6-7 Demand Data (Continued)

Units: Cubic Meters Per Second

Time	D12	D13	D14	D15	D16	D17	D18	D19	D20	D21
1	1.43	3.94	3.40	9.08	3.57	2.80	0.54	2.12	2.89	7.08
2	1.43	3.94	8.19	9.08	3.57	4.01	0.54	3.07	2.89	9.04
3	1.43	4.33	11.14	9.08	3.57	3.46	0.54	3.69	2.89	11.34
4	1.43	3.94	8.83	9.34	3.57	3.48	0.57	3.62	2.89	9.20
5	1.43	3.94	8.83	9.34	3.57	3.50	0.57	4.50	3.25	9.51
6	1.43	3.15	9.56	9.34	3.57	3.50	0.57	5.29	3.25	10.51
7	1.43	3.94	8.75	9.31	3.57	3.51	0.54	5.18	3.25	9.90
8	1.43	3.94	8.75	9.31	3.57	3.47	0.54	5.40	3.25	10.21
9	1.43	4.33	8.67	9.31	3.57	3.47	0.54	5.38	3.25	10.17
10	1.43	3.94	8.88	9.64	3.57	3.24	0.43	7.01	2.89	11.83
11	1.43	3.94	8.88	9.64	3.57	3.24	0.43	6.37	2.89	6.20
12	1.43	3.94	7.20	9.64	3.57	1.90	0.43	1.96	2.89	4.83
13	1.43	3.94	3.55	9.38	3.57	0.42	0.49	2.12	2.89	5.99
14	1.43	3.94	0.94	9.38	3.57	0.06	0.49	0.48	2.89	1.25
15	1.43	4.33	0.00	9.38	3.57	0.00	0.49	0.00	3.25	0.59
16	1.43	3.94	0.00	9.65	3.57	0.00	0.44	0.00	3.25	0.86
17	1.43	3.94	2.88	9.65	3.57	0.46	0.44	0.55	3.25	2.44
18	1.43	3.94	4.17	9.65	3.57	2.95	0.44	1.98	2.89	5.12
19	1.43	3.94	7.59	10.13	3.57	3.23	0.54	3.62	2.89	7.61
20	1.43	3.94	9.73	10.13	3.57	2.58	0.54	3.18	2.89	8.06
21	1.43	4.33	11.51	10.13	3.57	2.63	0.54	4.16	2.89	10.93
22	1.43	3.94	11.04	10.27	3.57	2.43	0.45	2.33	3.25	5.68
23	1.43	3.94	11.04	10.27	3.57	2.43	0.45	2.17	3.25	4.95
24	1.43	4.33	10.66	10.27	3.57	2.43	0.45	2.82	3.25	6.45
25	1.43	3.94	11.60	10.37	3.57	2.63	0.53	1.22	3.25	6.28
26	1.43	3.94	11.60	10.37	3.57	2.63	0.53	0.00	3.25	1.77
27	1.43	3.94	11.03	10.37	3.57	1.70	0.53	0.00	2.89	0.75
28	1.43	3.94	7.88	10.06	3.57	0.35	0.51	0.03	2.89	0.96
29	1.43	3.94	3.38	10.06	3.57	0.46	0.51	0.20	2.89	1.37
30	1.43	4.33	0.00	10.06	3.57	0.00	0.51	0.06	2.89	0.75
31	1.43	3.94	0.00	9.77	3.57	0.24	0.55	0.19	2.89	0.92
32	1.43	3.94	0.00	9.77	3.57	0.42	0.55	0.59	2.89	1.74
33	1.43	3.94	0.00	9.77	3.57	0.77	0.55	1.21	2.89	2.97
34	1.43	3.94	0.00	9.47	3.57	0.23	0.42	1.61	2.89	4.74
35	1.43	3.94	0.00	9.47	3.57	0.30	0.42	1.77	2.89	5.10
36	1.43	4.33	0.00	9.47	3.57	0.95	0.42	1.02	2.89	3.94

Table 6-8 The Optimal Zones of the Water Supply and Reservoir Beginning Storage (1984)

Time	T-W						Nanhwa	
	D1	D2	D3	D4	D5	Reservoir	D6	Reservoir
1	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2
3	2	2	2	2	2	2	2	2
4	2	2	2	2	2	2	2	2
5	1	1	1	1	1	1	2	2
6	1	1	1	1	1	1	2	2
7	1	1	1	1	1	1	2	2
8	1	1	1	1	1	1	2	2
9	1	1	1	1	1	1	2	2
10	2	2	2	2	2	2	2	2
11	2	2	2	2	2	2	2	2
12	1	1	1	1	1	1	2	2
13	3	3	3	3	3	3	2	2
14	3	3	3	3	3	3	3	3
15	3	3	3	3	3	3	3	3
16	2	2	2	2	2	2	3	3
17	2	2	2	2	2	2	2	2
18	2	2	2	2	2	2	2	2
19	2	2	2	2	2	2	2	2
20	3	3	3	3	3	3	3	3
21	2	2	2	2	2	2	3	3
22	1	1	1	1	1	1	3	3
23	1	1	1	1	1	1	3	3
24	1	1	1	1	1	1	3	3
25	1	1	1	1	1	1	3	3
26	1	1	1	1	1	1	3	3
27	1	1	1	1	1	1	3	3
28	1	1	1	1	1	1	3	3
29	1	1	1	1	1	1	3	3
30	1	1	1	1	1	1	2	2
31	1	1	1	1	1	1	3	3
32	1	1	1	1	1	1	2	2
33	1	1	1	1	1	1	2	2
34	1	1	1	1	1	1	3	3
35	1	1	1	1	1	1	2	2
36	1	1	1	1	1	1	2	2

Table 6-9 Sensitivity Analysis of Total Water Supply and Shortage to Rationing Factors

Units: Million Cubic Meters

Case	D1		D2		D3		D4		D5		D6	
	Su	Sh	Su	Sh	Su	Sh	Su	Sh	Su	Sh	Su	Sh
0	171.92	3.88	92.13	1.86	40.06	1.18	0.95	0.31	373.98	161.81	264.64	28.91
1-1	173.74	2.06	93.02	0.97	40.56	0.68	1.08	0.17	393.27	142.52	290.50	3.05
1-2	173.87	1.93	93.04	0.95	40.60	0.64	1.04	0.21	431.31	104.48	293.15	0.40
2-1	173.68	2.12	92.96	1.03	40.55	0.69	0.99	0.26	370.77	165.02	289.04	4.51
2-2	174.34	1.46	93.32	0.67	40.71	0.53	0.97	0.28	406.66	129.13	288.18	5.37
3-1	173.53	2.27	92.67	1.33	40.47	0.77	1.02	0.23	440.96	94.83	290.17	3.38
3-2	173.55	2.25	92.70	1.29	40.45	0.79	0.98	0.27	417.92	117.87	293.14	0.41

Case	D7		D8	
	Su	Sh	Su	Sh
0	14.58	0.18	69.98	0.68
1-1	14.76	0.00	70.57	0.09
1-2	14.76	0.00	70.66	0.00
2-1	14.76	0.00	70.66	0.00
2-2	14.76	0.00	70.66	0.00
3-1	14.76	0.00	70.66	0.00
3-2	14.76	0.00	70.66	0.00

Su: Total water supply.
Sh: Total shortage.

Case 0 (Current): (α_1=0.5, α_2=0.75) for agricultural demand, T-W; (α_1=0.8, α_2=1.0) for public demand, T-W; (α_1=0.8, α_2=0.9) for Nanhwa.
Case 1-1: (α_1=0.4, α_2=0.65) for agricultural demand, T-W; (α_1=0.7, α_2=0.9) for public demand, T-W; (α_1=0.7, α_2=0.8) for Nanhwa.
Case 1-2: (α_1=0.6, α_2=0.85) for agricultural demand, T-W; (α_1=0.9, α_2=1.0) for public demand, T-W; (α_1=0.9, α_2=1.0) for Nanhwa.
Case 2-1: (α_1=0.4, α_2=0.65) for agricultural demand, T-W; (α_1=0.7, α_2=0.9) for public demand, T-W; (α_1=0.8, α_2=0.9) for Nanhwa.
Case 2-2: (α_1=0.5, α_2=0.75) for agricultural demand, T-W; (α_1=0.8, α_2=1.0) for public demand, T-W; (α_1=0.7, α_2=0.8) for Nanhwa.
Case 3-1: (α_1=0.6, α_2=0.85) for agricultural demand, T-W; (α_1=0.9, α_2=1.0) for public demand, T-W; (α_1=0.8, α_2=0.9) for Nanhwa.
Case 3-2: (α_1=0.5, α_2=0.75) for agricultural demand, T-W; (α_1=0.8, α_2=1.0) for public demand, T-W; (α_1=0.9, α_2=1.0) for Nanhwa.

Table 6-10 Upper Bounds and Lower Bounds Used When Searching for New Rule Curves for T-W Reservoir and Nanhwa Reservoir

Time	T-W Reservoir				Nanhwa Reservoir			
	Firm Curve		Target Curve		Firm Curve		Target Curve	
	LB	UB	LB	UB	LB	UB	LB	UB
1	190.0	290.0	310.0	410.0	86.4	106.4	112.4	132.4
2	180.0	280.0	300.0	400.0	82.4	101.4	102.4	121.4
3	170.0	270.0	280.0	380.0	72.4	92.4	94.8	114.8
4	160.0	250.0	260.0	360.0	67.8	86.4	87.8	106.4
5	150.0	230.0	250.0	330.0	63.2	78.4	83.2	98.4
6	140.0	200.0	240.0	300.0	50.9	70.9	74.4	94.4
7	120.0	170.0	220.0	270.0	47.9	67.9	70.4	90.4
8	110.0	140.0	210.0	240.0	38.9	58.9	61.4	81.4
9	100.0	125.0	200.0	225.0	36.1	55.1	56.1	76.0
10	70.0	95.0	170.0	195.0	25.7	44.7	45.7	64.9
11	40.0	65.0	140.0	165.0	19.1	37.4	39.1	57.4
12	30.0	50.0	130.0	150.0	12.5	30.9	32.5	50.9
13	20.0	30.0	105.0	130.0	3.3	22.2	23.3	42.2
14	20.0	30.0	90.0	115.0	2.0	13.0	14.4	33.4
15	20.0	30.0	80.0	100.0	2.0	10.8	12.8	28.0
16	20.0	30.0	80.0	90.0	2.0	12.8	17.8	37.8
17	20.0	30.0	80.0	100.0	22.2	42.2	86.4	106.4
18	20.0	30.0	90.0	120.0	40.4	60.4	139.5	149.5
19	20.0	40.0	110.0	140.0	57.8	77.8	139.5	149.5
20	30.0	70.0	130.0	170.0	54.2	74.2	139.5	149.5
21	55.0	100.0	155.0	200.0	59.6	79.6	139.5	149.5
22	80.0	130.0	180.0	230.0	76.4	96.4	139.5	149.5
23	105.0	160.0	205.0	260.0	123.9	139.5	143.9	149.5
24	130.0	190.0	230.0	290.0	133.1	139.5	149.5	149.5
25	150.0	220.0	250.0	320.0	133.1	139.5	149.5	149.5
26	190.0	250.0	290.0	350.0	133.1	139.5	149.5	149.5
27	230.0	280.0	330.0	380.0	130.8	139.5	149.5	149.5
28	230.0	310.0	330.0	410.0	130.8	139.5	149.5	149.5
29	230.0	310.0	330.0	410.0	128.5	139.5	148.5	149.5
30	230.0	310.0	330.0	410.0	126.2	139.5	146.2	149.5
31	230.0	310.0	330.0	410.0	124.4	133.8	144.4	149.5
32	230.0	310.0	330.0	410.0	121.6	132.2	141.6	149.5
33	230.0	310.0	330.0	410.0	112.4	130.6	132.4	149.5
34	230.0	310.0	330.0	410.0	108.0	121.6	128.0	141.6
35	210.0	300.0	310.0	410.0	103.6	119.3	123.6	139.3
36	200.0	300.0	310.0	410.0	94.8	114.8	117.0	137.0

Table 6-11 Upper Bounds and Lower Bounds Used When Searching for New Rationing Factors for T-W Reservoir and Nanhwa Reservoir

Rationing Factors	T-W Reservoir				Nanhwa Reservoir	
	Agricultural Demand		Public Demand			
	LB	UB	LB	UB	LB	UB
α_1	0.40	0.60	0.75	0.85	0.75	0.85
α_2	0.65	0.85	0.85	1.00	0.85	0.95

Table 6-12 Comparison of System Operation Between the Current and New Rule Curves and Hedging Rules (1984)

Rule Curves and Hedging Rules	Objective Function Value	Number of 10-day Shortage	Water Supply (MCM)	Water Shortage (MCM)	Percentage of Shortage (%)
Current	−1331513	36	2061.95	630.13	23.41
New	−1370634	29	2236.31	455.77	16.93

Table 6-13 The Suggested Rule Curves for Dry Year Operation

Units: Million Cubic Meters

Time	T-W			Nanhwa	
	Firm Curve	Target Curve	Flood Control Curve	Firm Curve	Target Curve
1	190.00	390.00	500.00	86.40	112.40
2	200.00	320.35	480.00	90.00	103.25
3	210.00	300.00	460.00	84.40	96.29
4	178.00	272.20	440.00	75.24	87.80
5	182.00	266.00	420.00	69.28	83.20
6	152.00	252.00	400.00	58.90	74.40
7	130.00	230.00	380.00	55.90	73.44
8	116.00	210.00	360.00	46.90	61.40
9	105.00	205.00	340.00	46.30	56.10
10	80.00	175.00	320.00	33.30	45.70
11	45.00	140.00	300.00	26.42	42.76
12	38.00	134.00	280.00	19.86	32.50
13	22.00	110.00	260.00	18.42	23.30
14	24.00	90.00	240.00	6.40	14.40
15	22.00	81.68	220.00	5.52	12.80
16	26.00	81.95	220.00	6.32	21.80
17	24.00	84.00	220.00	34.20	86.40
18	22.00	102.00	230.00	44.40	141.50
19	24.00	110.00	250.00	62.80	139.50
20	38.00	130.00	300.00	62.20	139.50
21	64.00	191.00	360.00	79.60	139.50
22	80.00	220.00	420.00	84.40	139.50
23	105.00	249.00	460.00	130.14	143.90
24	130.00	254.00	581.00	135.66	149.50
25	164.00	292.00	617.00	136.94	149.50
26	202.00	314.00	617.00	136.94	149.50
27	240.00	336.28	617.00	130.80	149.50
28	238.20	339.38	617.00	130.80	149.50
29	232.23	335.54	617.00	132.90	148.50
30	240.29	338.51	617.00	126.20	146.86
31	230.00	362.00	617.00	128.16	144.40
32	230.00	362.00	580.00	132.20	141.60
33	230.00	362.00	570.00	119.68	132.40
34	246.00	362.00	560.00	113.44	128.00
35	210.00	350.00	540.00	114.30	123.60
36	220.00	350.00	520.00	102.80	117.00

Table 6-14 The Suggested Hedging Rules of the T-W Reservoir for Dry Year Operation

Reservoir Storage	Rationing Factor	
	Agricultural Demand	Public Demand
Minimum Storage ≤ $S_{T,t} + S_{W,t}$ < Firm Storage	44%	83%
Firm Storage ≤ $S_{T,t} + S_{W,t}$ < Target Storage	66%	98%
Target Storage ≤ $S_{T,t} + S_{W,t}$	100%	100%

$S_{T,t}$: Beginning storage of the Tsengwen Reservoir in time period t.
$S_{W,t}$: Beginning storage of the Wusantou Reservoir in time period t.

Table 6-15 The Suggested Hedging Rules of the Nanhwa Reservoir for Dry Year Operation

Reservoir Storage	Rationing Factor
Minimum Storage ≤ $S_{N,t}$ < Firm Storage	85%
Firm Storage ≤ $S_{N,t}$ < Target Storage	95%
Target Storage ≤ $S_{N,t}$	100%

$S_{N,t}$: Beginning storage of the Nanhwa Reservoir in time period t.

Table 6-16 The Suggested Rule Curves for Normal Year Operation

Units: Million Cubic Meters

Time	T-W			Nanhwa	
	Firm Curve	Target Curve	Flood Control Curve	Firm Curve	Target Curve
1	210.00	390.00	500.00	101.40	112.40
2	240.00	310.00	480.00	99.50	102.40
3	240.00	280.00	460.00	90.40	94.80
4	223.00	260.00	440.00	84.54	87.80
5	206.00	250.00	420.00	76.88	83.20
6	182.00	240.00	400.00	68.90	74.40
7	150.00	220.00	380.00	65.90	72.40
8	128.00	210.00	360.00	56.90	61.40
9	115.00	200.00	340.00	55.10	56.10
10	85.00	170.00	320.00	42.80	45.70
11	55.00	140.00	300.00	35.57	39.10
12	42.00	130.00	280.00	29.06	32.50
13	26.00	105.00	260.00	22.20	23.30
14	26.00	90.00	240.00	11.90	14.40
15	26.00	80.00	220.00	9.92	12.80
16	26.00	80.00	220.00	11.72	17.80
17	26.00	80.00	220.00	40.20	86.40
18	26.00	90.00	230.00	58.40	139.50
19	32.00	113.00	250.00	75.80	139.50
20	54.00	134.00	300.00	72.20	139.50
21	55.00	200.00	360.00	79.60	139.50
22	110.00	190.00	420.00	94.40	139.50
23	138.00	216.00	460.00	139.50	143.90
24	149.22	242.00	581.00	138.22	149.50
25	192.00	257.00	617.00	138.22	149.50
26	226.00	296.00	617.00	139.50	149.50
27	237.23	331.03	617.00	130.80	149.50
28	232.06	330.00	617.00	130.80	149.50
29	231.07	330.00	617.00	129.60	148.70
30	230.44	330.00	617.00	128.86	146.72
31	263.00	346.00	617.00	132.86	144.40
32	254.00	338.00	580.00	132.20	141.60
33	246.00	338.00	570.00	128.78	132.40
34	238.00	338.00	560.00	120.24	128.00
35	228.00	320.00	540.00	119.30	123.60
36	210.22	320.00	520.00	112.80	117.00

Table 6-17 The Suggested Hedging Rules of the T-W Reservoir for Normal Year Operation

Reservoir Storage	Rationing Factor	
	Agricultural Demand	Public Demand
Minimum Storage $\leq S_{T,t} + S_{W,t}$ < Firm Storage	45%	84%
Firm Storage $\leq S_{T,t} + S_{W,t}$ < Target Storage	69%	98%
Target Storage $\leq S_{T,t} + S_{W,t}$	100%	100%

$S_{T,t}$: Beginning storage of the Tsengwen Reservoir in time period t.
$S_{W,t}$: Beginning storage of the Wusantou Reservoir in time period t.

Table 6-18 The Suggested Hedging Rules of the Nanhwa Reservoir for Normal Year Operation

Reservoir Storage	Rationing Factor
Minimum Storage $\leq S_{N,t}$ < Firm Storage	81%
Firm Storage $\leq S_{N,t}$ < Target Storage	95%
Target Storage $\leq S_{N,t}$	100%

$S_{N,t}$: Beginning storage of the Nanhwa Reservoir in time period t.

Table 6-19 Average Annual Water Shortage Comparison of Current and Suggested Rule Curves and Hedging rules

Rule Curves and Hedging Rules	Average Annual Water Shortage (MCM)	
	Dry Year	Normal Year
Current Setting	697.76	434.90
Suggested Setting	650.58	375.26

Figure 6-1 Area Covered by the Southern Regional System, Taiwan

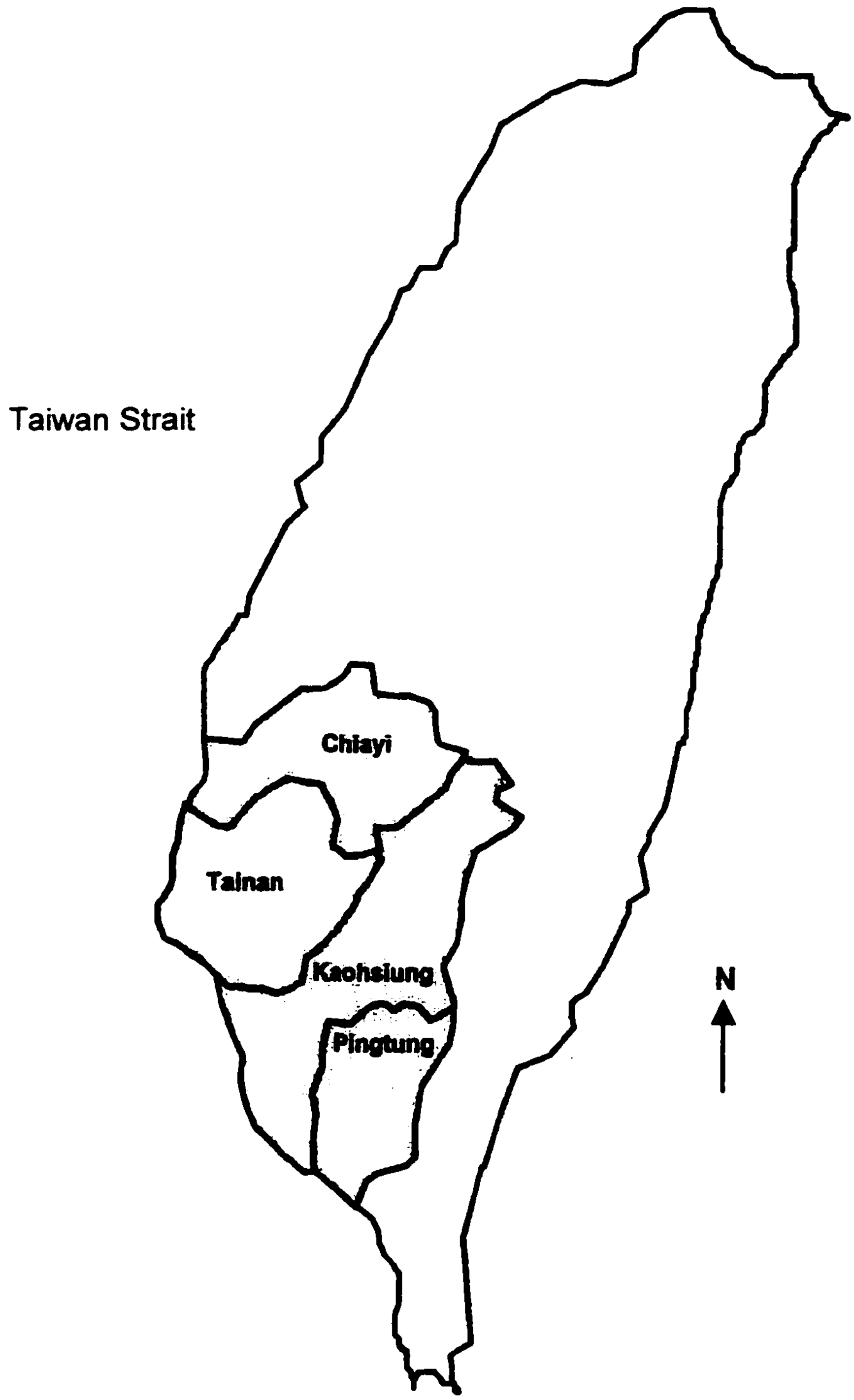


Figure 6-2 Layout of Water Resources in the Southern Regional System, Taiwan

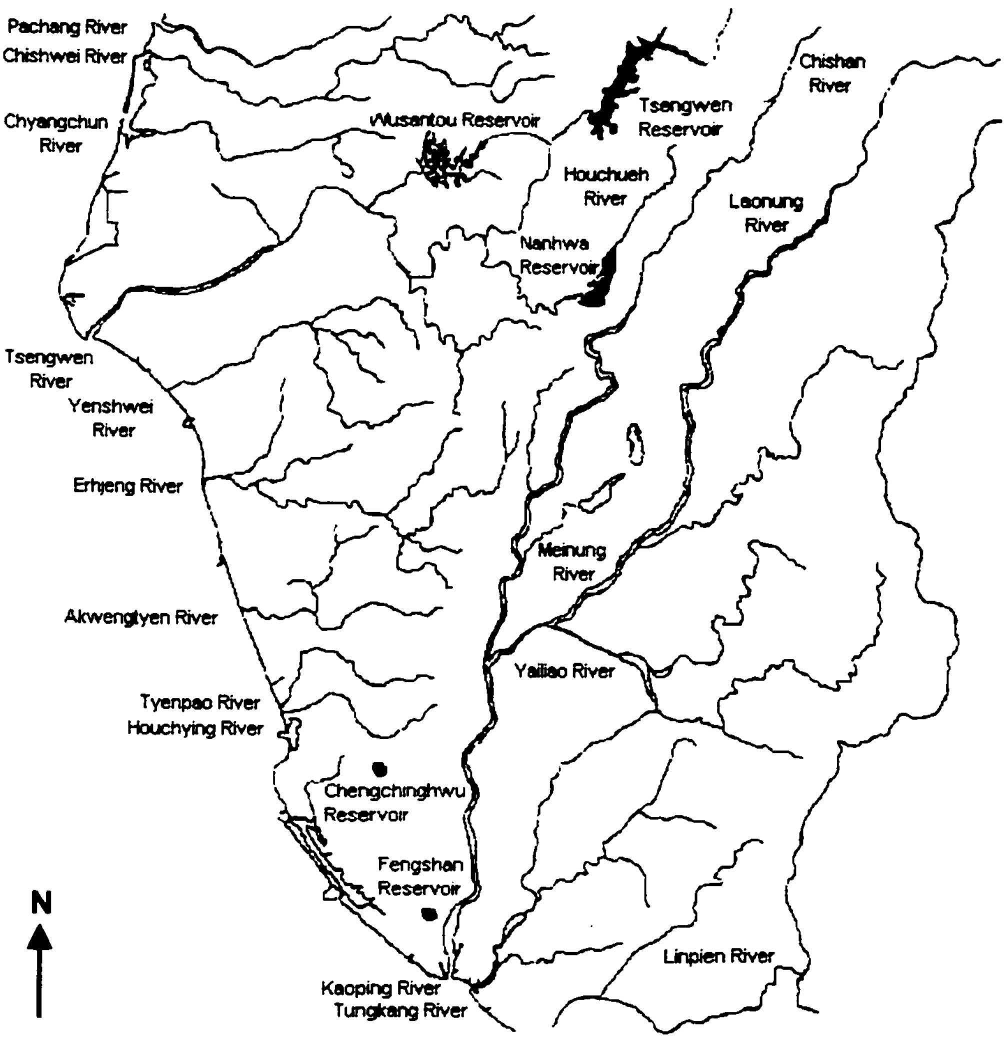


Figure 6-3 Network Representation of Southern Regional System, Taiwan

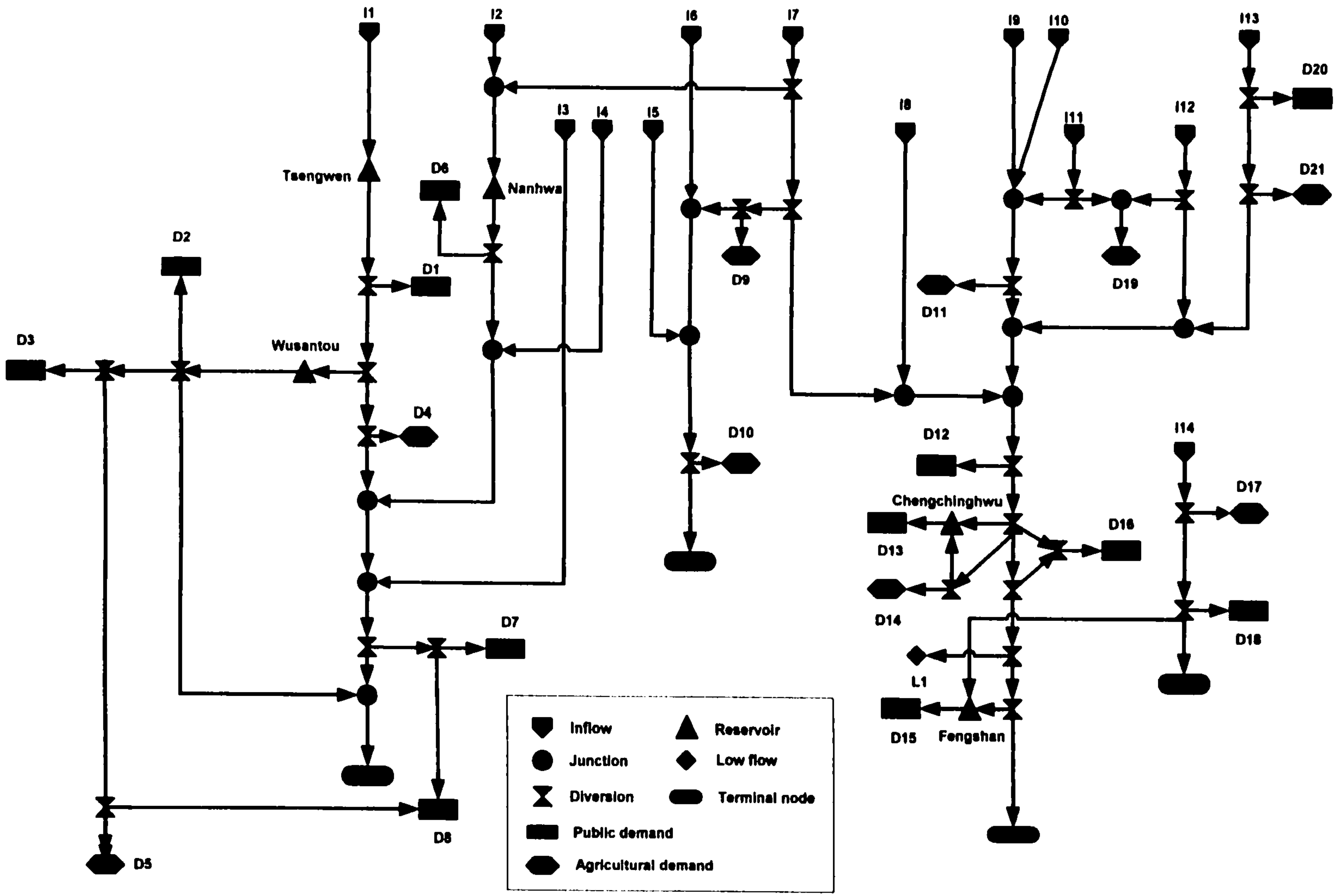


Figure 6-4 Average Annual Inflow in the Southern Region

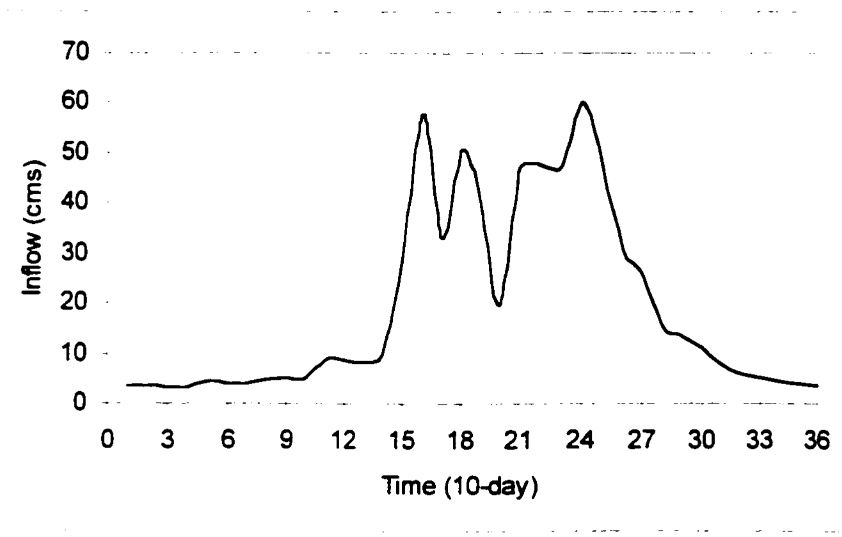
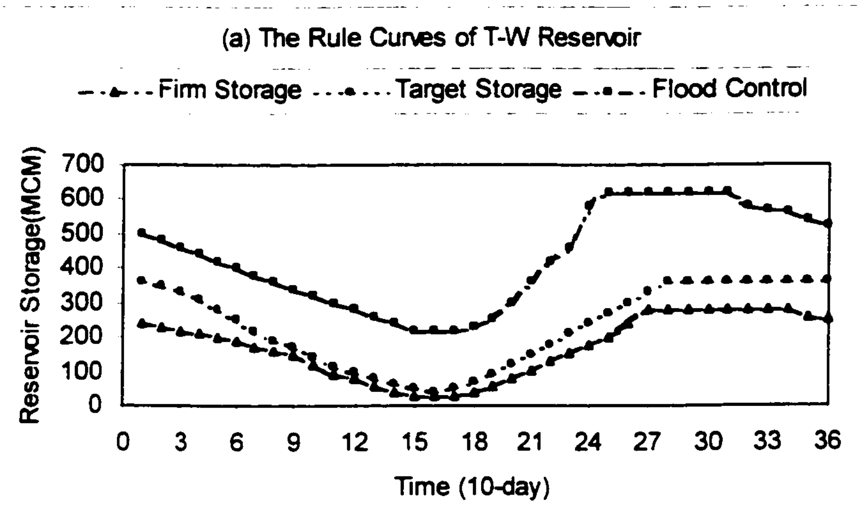


Figure 6-5 Rule Curves of the T-W Reservoir and Nanhwa Reservoir



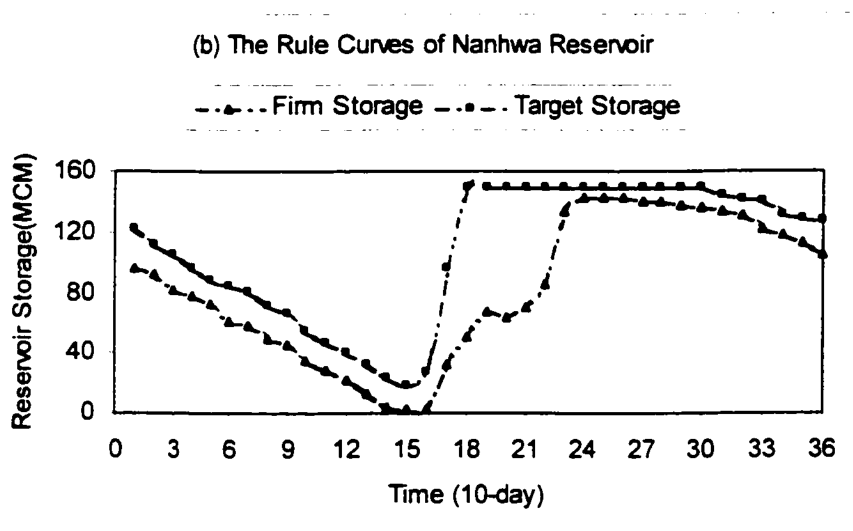


Figure 6-6 Network Transformation for Low Flow Node

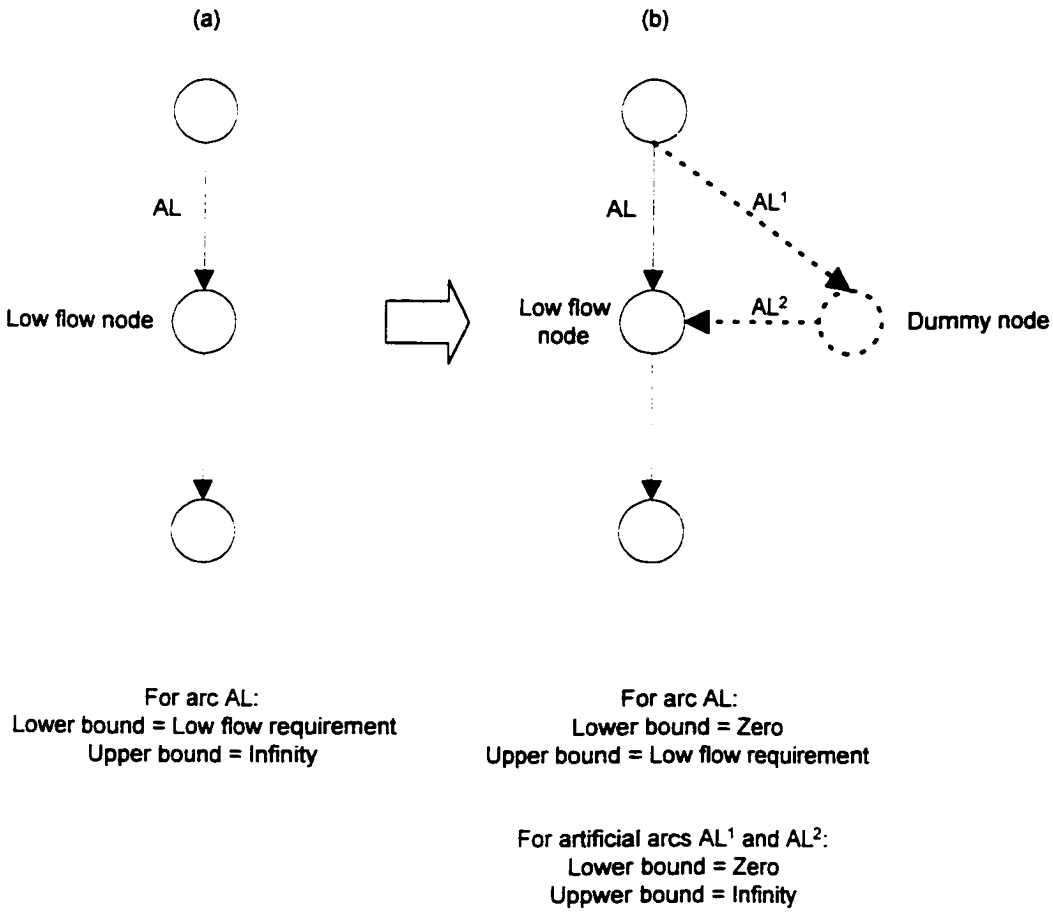


Figure 6-7 Annual Inflow in the Southern Region

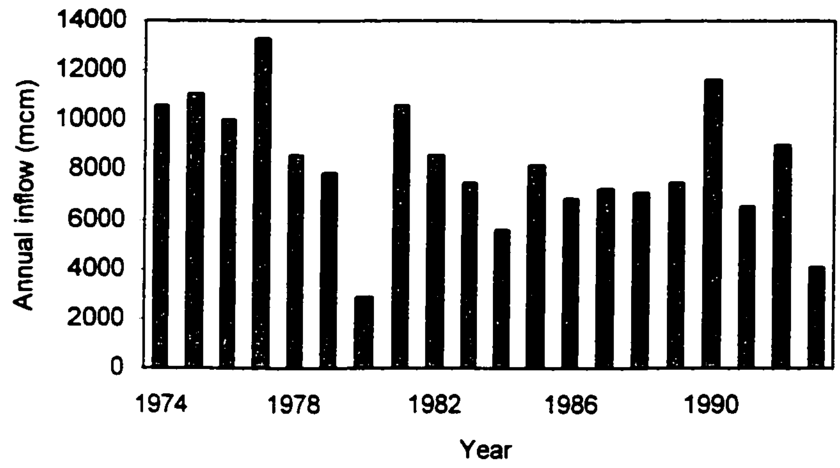


Figure 6-8 The Optimized Results

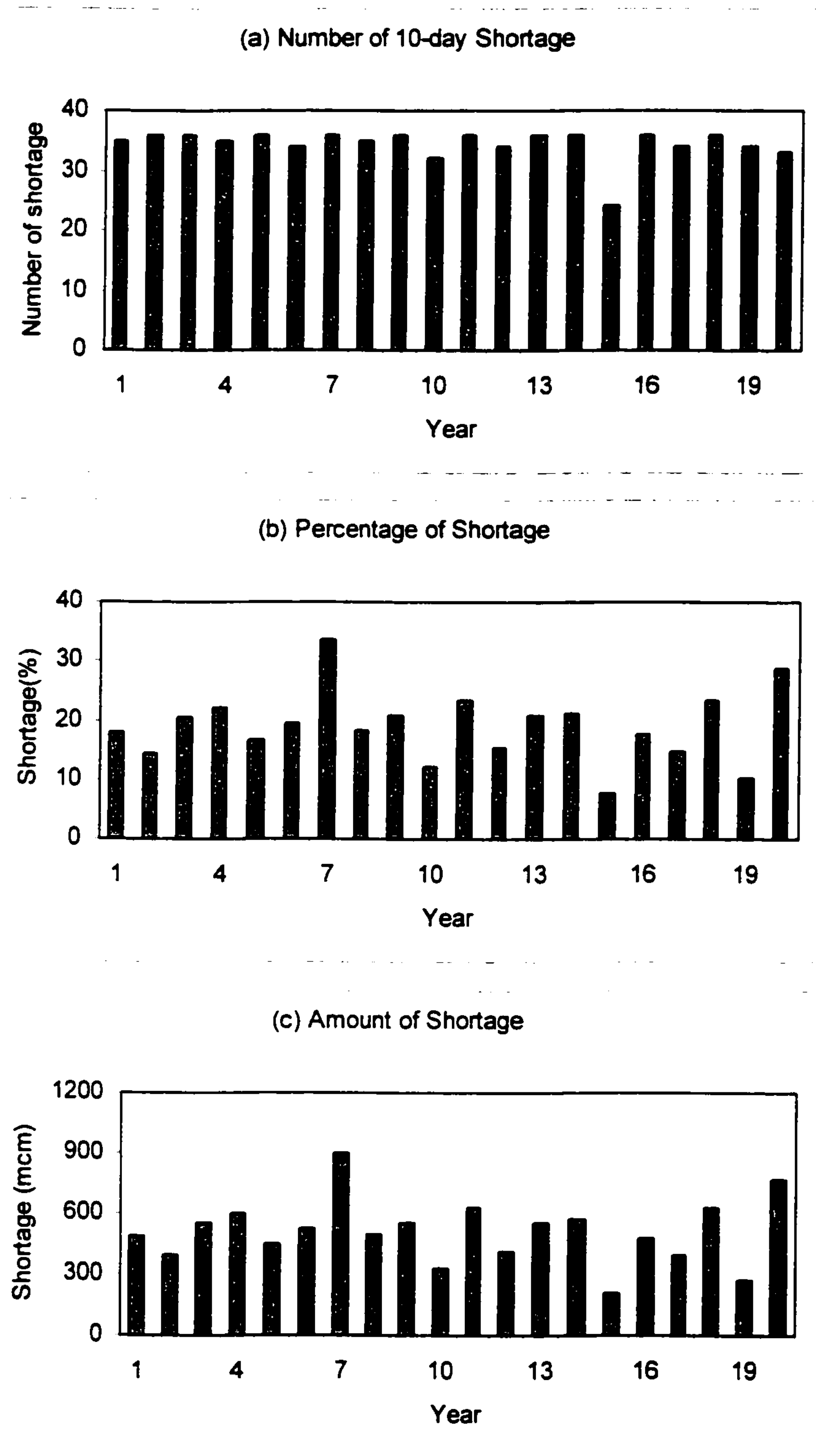
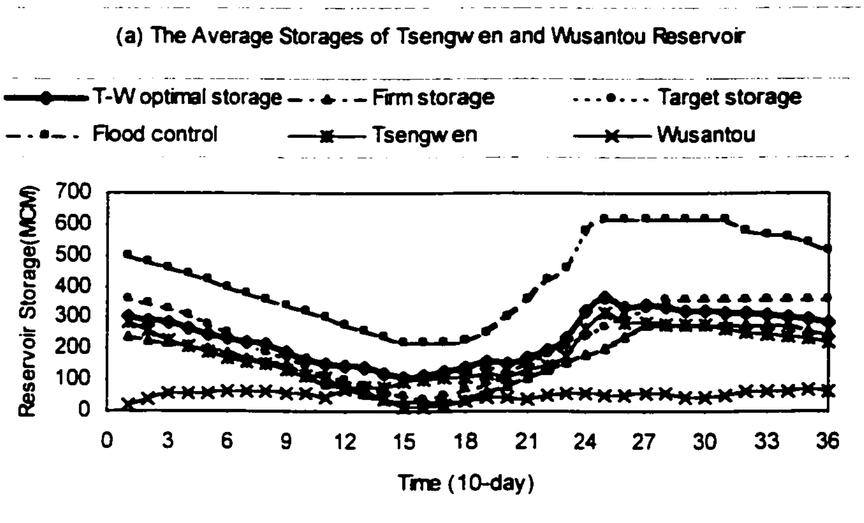


Figure 6-9 The Optimized Long-term Reservoir Storage



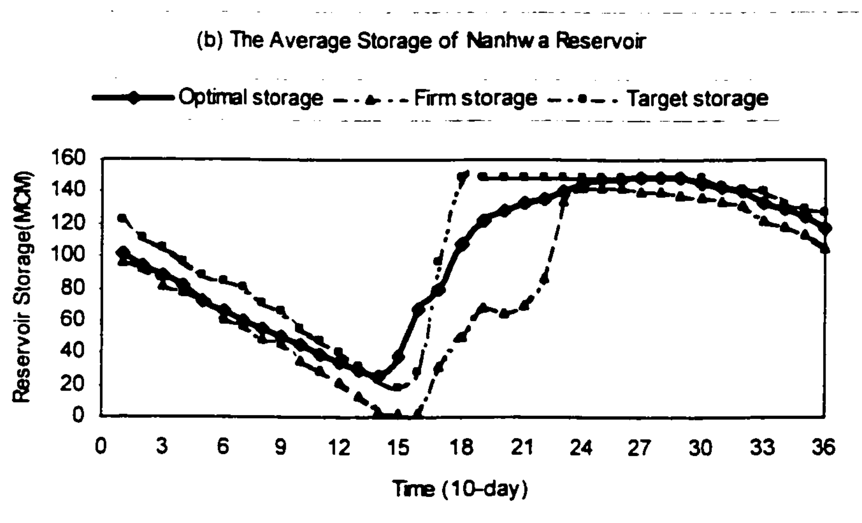


Figure 6-10 The Optimized Long-term Demand and Supply

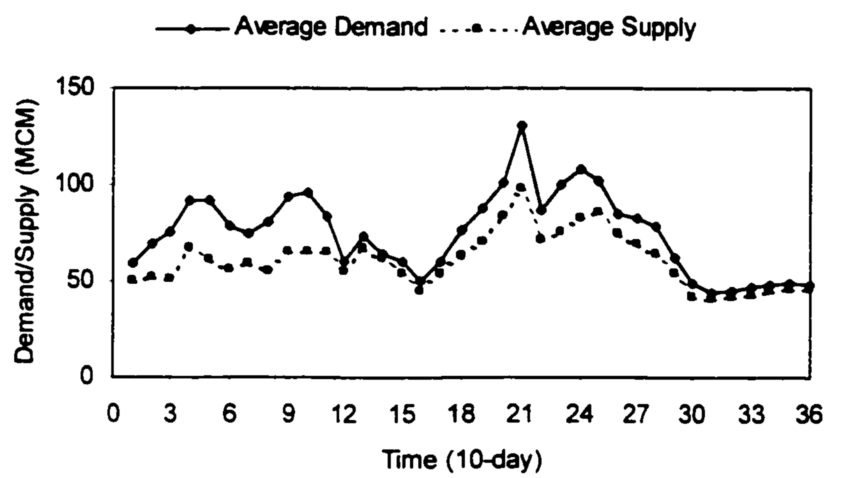
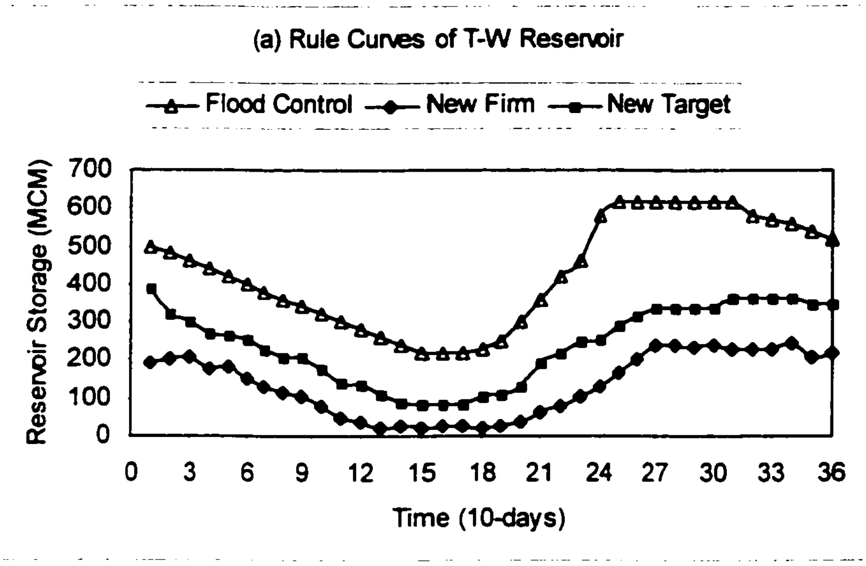


Figure 6-11 The Suggested Rule Curves for Dry Year Operation



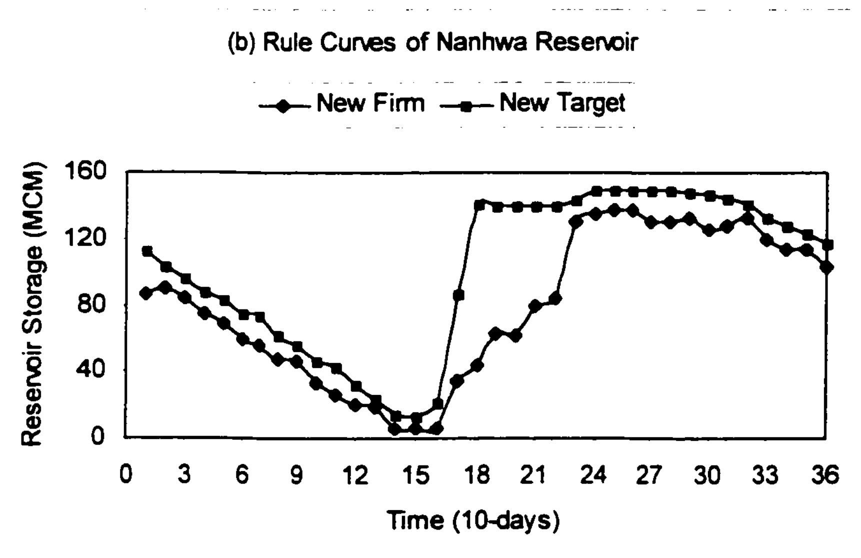
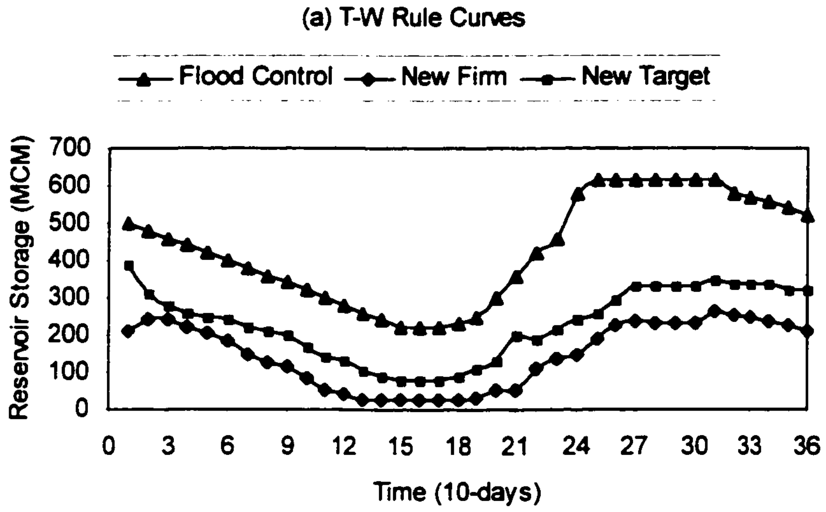
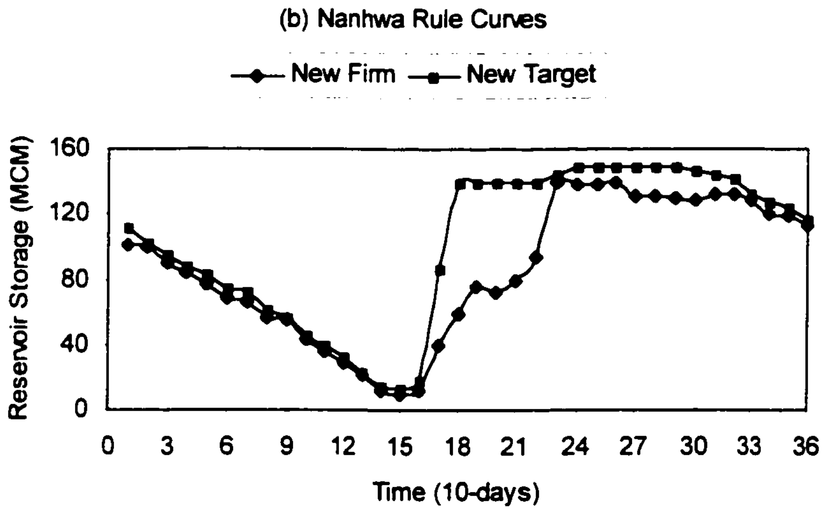


Figure 6-12 The Suggested Rule Curves for Normal Year Operation





CHAPTER 7 CONCLUSIONS AND FUTURE RESEARCH

Reservoir management and operation play an important rule in overall water resources planning and management. During normal periods of operation, allocating the available water from different reservoirs to meet the planned demands imposed by competing users can be achieved without difficulty. However, during periods of drought, or when anticipating a drought, water demand cannot be met 100% and water shortages occur. The reservoir rule curves and the hedging rules provide operating guidelines that can be followed to minimize the impacts of a drought when water in the reservoirs are depleted because of insufficient inflows.

This study focuses on incorporating the rule curves and hedging rules in the optimization of reservoir management and operation. Furthermore, compared with the current setting, a superior set of rule curves and hedging rules are achieved to improve the current system operation. The conclusions and future research of this study will be described in the following sections.

7.1 Conclusions

Listed below are a number of conclusions reached by this study:

1. A multi-reservoir, multi-purpose MILP model that considers both the rule curves and the hedging rules is developed for optimizing a large-scale regional water distribution

system. The developed model was tested and verified on a simplified system. Then this model was successfully applied to the regional water distribution system in the southern region of Taiwan. The results obtained demonstrated the applicability and utility of the proposed MILP model. A manuscript summarizing the results has been accepted for publication (Tu et al., 2002).

2. A MINLP model is developed by expanding the proposed MILP model to achieve the new reservoir rule curves and hedging rules to improve the current reservoir operation. By applying this model to the simplified system, the new rule curves and hedging rules obtained are demonstrated to be superior. Then this methodology was successfully applied to the regional water distribution system in the southern region of Taiwan to achieve new rule curves and hedging rules. The results showed that the performance of system operation could be improved if the new rule curves and hedging rules are implemented. In addition, two types of rule curves and hedging rules, dry year and normal year, are proposed for realistic multi-reservoir system operation for different hydrology situations.

3. To solve the presented MINLP model which is a nonconvex optimization problem, a number of methodologies are proposed. These methodologies are: Generalized Benders Decomposition, Penalty Coefficient Methods, Pseudo-integer Method, Simulated Annealing, and one mathematical transformation technique. The advantages and drawbacks of these methodologies are pointed out in the previous discussion. A comparison of these methodologies reveals that the transformation technique takes advantage of the mathematical structure and is most suitable to

solving the presented MINLP model.

4. In order to determine a set of rule curves and hedging rules for a multi-purpose reservoir, numerous affecting factors such as the system hydrology characteristics, reservoir operating purposes, water supply for planned demands, and orderly rule curves, need to be considered. Consequently, not only a mathematical optimization model is necessary for decision making, but also the establishment of a cooperative relationship between the system managers, reservoir operators and water users.
5. When a set of rule curves and hedging rules are determined, they may not be applicable for the reservoir after years of operation. Therefore, it is necessary to modify the rule curves and hedging rules from time to time to optimize the reservoir operation.

7.2 Future Research

Several works for future research are suggested based on the discussion of this study:

1. Future studies may consider the hydraulic uncertainty to analyze the reliability of new rule curves and hedging rules for reservoir management and operation.
2. The use of ground water may be considered to supplement the surface water supply.
3. More system characteristics may be taken into account to improve the proposed optimization models. These characteristics include: reservoir evaporation, reservoir storage change with time, loss/gains during water transshipment, and so on.

4. In general, the pattern of hedging consists of two or three rules curves with corresponding rationing factors for a multi-purpose reservoir. This kind of pattern may need to be reevaluated (such as introducing four rule curves) for better reservoir operation performance.

REFERENCES

Aarts, E. H. L., and Van Laarhoven, P. J. M. (1985). "Statistical cooling: A general approach to combinatorial optimization problems." *Philips J. Res.* 40(4), 193-226.

Ahuja, R. K., Magnanti, T. L., and Orlin, J. B. (1993). *Network Flows*, Prentice-Hall, Upper Saddle River, New Jersey.

Alonso, J. M., Alvarruiz, F., Guerrero, D., Hernandez, V., Ruiz, P. A., Vidal, A. M., Martinez, F., Vercher, J., and Ulanicki, B. (2000). "Parallel computing in water network analysis and leakage minimization." *J. Water Resour. Plng. and Mgmt.*, ASCE, 126(4), 251-260.

Bach, N. L., Fujiwara, O., and Luong, H. T. (2000). "Optimal fund assignment and allocation models for pipe repair maintenance in leaky water distribution networks." *Water Resour. Res.*, 36(5), 1315-1324.

Bagajewicz, M. J., and Manousiouthakis, V. (1991). "On the generalized benders decomposition." *Comput. chem. Engng.*, 15(10), 691-700.

Benders, J. F. (1962). "Partitioning procedures for solving mixed-variables programming proglems." *Numer. Math.*, 4, 238-252.

Bhaskar, N. R., and Whitlatch, E. E. Jr. (1980). "Derivation of monthly reservoir release policies." *Water Resour. Res.*, 16(6), 987-993.

Cai, X., McKinney, D. C., Lasdon, L. S., and Watkins, Jr, D. W. (2001). "Solving large nonconvex water resources management models using generalized Benders decomposition." *Ops. Res.*, 49(2), 235-245.

Cai, X., McKinney, D. C., and Lasdon, L. S. (2001). "Solving nonlinear water management models using a combined genetic algorithm and linear programming approach." *Adv. Water Res.*, 24, 667-676.

Chen, L. (1995). *A study of optimizing the rule curve of reservoir using objective oriented genetic algorithms*, Ph.D. dissertation, National Taiwan University, Taipei, Taiwan. (In Chinese)

Chency, E. W., and Goldstein, A. A. (1959). "Newton's method for convex programming and Tchebycheff approximation." *Numer. Math.*, 1, 253-268.

Corana, A., Marchesi, M., Martini, C., and Ridella, S. (1987). "Minimizing multimodal functions of continuous variables with the "simulated annealing" algorithm." *ACM Transactions on Mathematical Software*, 13(3), 262-280.

Cunha, M. C., and Sousa, J. (1999). "Water distribution network design optimization: simulated annealing approach." *J. Water Resour. Plng. and Mgmt.*, ASCE, 125(4), 215-221.

Diba, A., Louie, P. W. F., Mahjoub, M., and Yeh, W. W-G. (1995). "Planned operation of large-scale water-distribution system." *J. Water Resour. Plng. and Mgmt.*, ASCE, 121(3), 260-269.

Dougherty, D. E., and Marryott, R. A. (1991). "Optimal groundwater management – 1. Simulated annealing." *Water Resour. Res.*, 27(10), 2493-2508.

Drud, A. S. (1994). "CONOPT – A large-scale GRG code." *ORSA J. Comput.*, 6(2), 207-216.

Duran, M. A., and Grossmann, I. E. (1986a). "An outer-approximation algorithm for a class of mixed-integer nonlinear programs." *Math. Prog.*, 36, 307-339.

Duran, M. A., and Grossmann, I. E. (1986b). "A mixed-integer nonlinear programming algorithm for process systems synthesis." *AIChE J.*, 32(4), 592-606.

Floudas, C. A., Aggarwal, A., and Ciric, A. R. (1989). "Global optimum search for nonconvex NLP and MINLP problems." *Comput. chem. Engng.*, 13(10), 1117-1132.

Floudas, C. A. (1995). *Nonlinear and Mixed-Integer Optimization*, Oxford Univ. Press, New York.

Geoffrion, A. M. (1972). "Generalized Benders decomposition." *J. Optim. Theory and Appl.*, 10(4), 237-260.

Goffe, W. L., Ferrier, G. D., and Rogers, J. (1994). "Global optimization of statistical functions with simulated annealing". *Journal of Econometrics*, 60, 65-99.

Goldberg, D. E., and Kuo, C. H. (1987). "Genetic algorithms in pipeline optimization." *J. Comp. in Civ. Engrg.*, ASCE, 1(2), 128-141.

Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, Reading, Mass.

Gomory, R. E. (1958). "Outline of an algorithm for integer solutions to linear programs." *Bull. Am. Math. Soc.*, 64(5), 275-278.

Gomory, R. E. (1960). "Solving linear programming problems in integers." in *Combinatorial Analysis*, edited by R. Bellman and M. Hall, Providence, 211-215.

Guercio, R., and Xu, Z. (1997). "Linearized optimization model for reliability-based design of water systems." *J. Hydraul. Eng.*, ASCE, 123(11), 1020-1026.

Halhal, D., Walters, G. A., Ouazar, D., and Savic, D. A. (1997). "Water network rehabilitation with structured messy genetic algorithm." *J. Water Resour. Plng. and Mgmt.*, ASCE, 123(3), 137-198.

Hsu, N.-S., and Yeh, W. W-G. (1989). "Optimum experimental design for parameter identification in groundwater hydrology." *Water Resour. Res.*, 25(5), 1025-1040.

Hsu, N.-S., and Yeh, W. W-G. (1992). *A Mathematical Programming Procedure Using Dantzig-Wolfe Decomposition for Facility Planning of Water Distribution System*, Department of Civil Engineering, UCLA, Los Angeles, California.

Hsu, N.-S., and Cheng, K.-W. (2002). "Network flow optimization model for basin scale water supply planning." *J. Water Resour. Plng. and Mgmt.*, ASCE, 128(2), 102-112.

Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, MI.

Huang, M. D., Romeo, F., and Sangiovanni-Vincentelli, A. (1986). "An efficient general cooling schedule for simulated annealing." *Proceedings of the IEEE International Conference on Computer-Aided Design*, Santa Clara, CA, 381-384.

Jacobs, J., Freeman, G., Grygier, J., Morton, D., Schultz, G., Staschus, K., and Stedinger, J. (1995). "A stochastic multi-reservoir hydroelectric scheduling model." *Proceedings of the 22nd annual conference on Integrated Water Resources Planning for the 21st century*, ASCE, Cambridge, MA., 828-831.

Jain, S. K., Goel, M. K., and Agarwal, P. K. (1998). "Reservoir operation studies of Sabarmati System, India." *J. Water Resour. Plng. and Mgmt.*, ASCE, 124(1), 31-38.

Johnson, D. S., Aragon, C. R., McGeoch, L. A., and Schevon, C. (1989). "Optimization by simulated annealing: An experimental evaluation; Part 1, Graph partitioning." *Ops. Res.*, 37(6), 865-892.

Karamouz, M., and Houck, M. H. (1982). "Annual and monthly reservoir operating rules generated by deterministic optimization." *Water Resour. Res.*, 18(5), 1337-1344.

Karatzas, G. P., and Pinder, G. F. (1993). "Groundwater management using numerical simulation and the outer approximation method for global optimization." *Water Resour. Res.*, 29(10), 3371-3378.

Kelley, J. E. (1960). "The cutting-plane method for solving convex problems." *J. Soc. Indust. Appl. Math.*, 8(4), 703-712.

Kim, J. H., and Mays, L. W. (1994). "Optimal rehabilitation model for water-distribution systems." *J. Water Resour. Plng. and Mgmt.*, ASCE, 120(5), 674-692.

Kirkpatrick, S., Gelatt, C. D., and Vecchi, M. P. (1983). "Optimization by simulated annealing." *Sci.*, 220(4598), 671-680.

Kirkpatrick, S. (1984). "Optimization by simulated annealing: Quantitative studies." *J. Stat. Phys.*, 34(5/6), 975-986.

Kuczera, G. (1989). "Fast multireservoir multiperiod linear programming models." *Water Resour. Res.*, 25(2), 169-176.

Kwanyuen, B., and Fontane, D. G. (1998). "Heuristic branch-and-bound method for ground water development planning." *J. Water Resour. Plng. and Mgmt.*, ASCE, 124(3), 140-148.

Lall, U., and Santini, M. D. (1989). "An optimization model for unconfined stratified aquifer systems." *J. Hydrol.*, 111, 145-162.

Lasdon, L. S., and Waren, A. D. (1978). "Generalized reduced gradient software for linearly and nonlinearly constrained problems." in Design and Implementation of Optimization Software, Greenberg, H. J., (Ed.), Sijthoff and Noordhoff, Holland, 335-362.

Lindo systems Inc. (1999). "LINGO 6.0 user's guide."

Loganathan, G. V., Greene, J. J., and Ahn, T. J. (1995). "Design heuristic for globally minimum cost water-distribution systems." *J. Water Resour. Plng. and Mgmt.*, ASCE, 121(2), 182-192.

Loucks, D. P., Stedinger, J. R., and Haith, D. A. (1981). *Water resources systems planning and analysis*, Prentice-Hall, Englewood Cliffs, New Jersey.

Marryott, R. A., Dougherty, D. E., and Stollar, R. L. (1993). "Optimal groundwater management – 2. Application of simulated annealing to a field-scale contamination site." *Water Resour. Res.*, 29(4), 847-860.

Mauldon, A. D., Karasaki, K., Martel, S. J., Long, J. C. S., Landsfeld, M., Mensch, A., and Vomvoris, S. (1993). "An inverse technique for developing models for fluid flow in fracture system using simulated annealing." *Water Resour. Res.*, 29(11), 3775-3789.

Mays, L. W., and Tung, Y.-K. (1992). *Hydrosystems engineering and management*, McGraw-Hill, Hightstown, New Jersey.

McKinney, D. C., and Lin, M.-D. (1994). "Genetic algorithm solution of groundwater management models." *Water Resour. Res.*, 30(6), 1897-1906.

McKinney, D. C., and Lin, M.-D. (1995). "Approximate mixed-integer nonlinear programming methods for optimal aquifer remediation design." *Water Resour. Res.*, 31(3), 731-740.

Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., and Teller, E. (1953). "Equation of state calculations by fast computing machines." *J. Chem. Phys.*, 21, 1087-1090.

Momoh, J. A., El-Hawary, M. E., and Adapa, R. (1999a). "A review of selected optimal power flow literature to 1993, Part I: NonLinear and Quadratic Programming Approaches." *IEEE Transactions on Power Systems*, 14(1), 96-104.

Momoh, J. A., El-Hawary, M. E., and Adapa, R. (1999b). "A review of selected optimal power flow literature to 1993, Part II: Newton, Linear Programming and Interior Point Methods." *IEEE Transactions on Power Systems*, 14(1), 105-111.

Montesinos, P., Garcia-Guzman, A., and Ayuso, J. L. (1999). "Water distribution network optimization using a modified genetic algorithm *Water Resour. Res.*, 35(11), 3467-3473.

Murtagh, B. A., and Saunders, M. A. (1982). "A projected Lagrangian algorithm and its implementation for sparse nonlinear constraints." *Math. Programming Study*, 16, 84-117.

Murty, K. G., and Kabadi, S. N. (1987). "Some NP-complete problems in quadratic and nonlinear programming." *Math. Progr.* 39(2), 117-129.

Neelakantan, T. R., and Pundarikanthan, N. V. (2000). "Neural network-based simulation-optimization model for reservoir operation" *J. Water Resour. Plng. and Mgmt.*, ASCE, 126(2), 57-64.

Nemhauser, G. L. and Wolsey, L. A. (1988). *Integer and Combinatorial Optimization*, John Wiley & Sons, New York.

Oliveira, R., and Loucks, D. P. (1997). "Operating rules for multireservoir systems." *Water Resour. Res.*, 33(4), 839-852.

Ostfeld, A., and Shamir, U. (1993a). "Optimal operation of multiquality networks, I: Steady-state conditions." *J. Water Resour. Plng. and Mgmt.*, ASCE, 119(6), 645-662.

Ostfeld, A., and Shamir, U. (1993b). "Optimal operation of multiquality networks, II: Unsteady conditions." *J. Water Resour. Plng. and Mgmt.*, ASCE, 119(6), 663-684.

Ostfeld, A., and Shamir, U. (1996). "Design of optimal reliable multiquality water-supply systems." *J. Water Resour. Plng. and Mgmt.*, ASCE, 122(5), 322-333.

Papadimitriou, C. H., and Steiglitz, K. (1998). *Combinatorial optimization*, Dover Publications, Mineola, New York.

Pham, D. T., and Karaboga, D. (2000). *Intelligent Optimisation Techniques – Genetic Algorithms, Tabu Search, Simulated Annealing and Neural Networks*. Springer.

ReVelle, C. (1997). Water Resources: Surface Water Systems, Chapter 1 In C. ReVelle and A.E. McGarity Edited, *Design and Operation of Civil and Environmental Engineering Systems*, Wiley-Interscience, New York, 1-39.

Ritzel, B. J., and Eheart, J. W. (1994). "Using genetic algorithms to solve a multiple objective groundwater pollution containment problem." *Water Resour. Res.*, 30(5), 1589-1603.

Sand, G. M. (1984). *An analytical investigation of operating policies for water-supply reservoirs in parallel*, Ph.D. dissertation, Cornell Univ., Ithaca, New York.

Savic, D. A., and Walters, G. A. (1997). "Genetic algorithms for least-cost design of water distribution networks." *J. Water Resour. Plng. and Mgmt.*, ASCE, 123(2), 67-77.

Shih, J.-S., and ReVelle, C. (1994). "Water-supply operations during drought: Continuous hedging rules." *J. Water Resour. Plng. and Mgmt.*, ASCE, 120(5), 613-629.

Shih, J.-S., and ReVelle, C. (1995). "Water-supply operations during drought: A discrete hedging rule." *Eur. J. Operational Res.*, 82, 163-175.

Simonovic, S. P. (1992). "Reservoir systems analysis: Closing gap between theory and practice." *J. Water Resour. Plng. and Mgmt.*, ASCE, 118(3), 262-280.

Simpson, A. R., Dandy, G. C., and Murphy, L. J. (1994). "Genetic algorithms compared to other techniques for pipe optimization." *J. Water Resour. Plng. and Mgmt.*, ASCE, 120(4), 423-443.

Skaggs, R. L., Mays, L. W., and Vail, L. W. (2001). "Simulated annealing with memory and directional search for ground water remediation design." *Journal of the American Water Resources Association*, 37(4), 853-866.

Su, Y.-C., Mays, L. W., Duan, N., and Lansey, K. E. (1987). "Reliability-based optimization model for water distribution systems." *J. Hydraul. Eng.*, ASCE, 114(12), 1539-1556.

Sun, Y.-H., Yeh, W. W-G., Hsu, N.-S., and Louie, P. W. F. (1995). "Generalized network algorithm for water-supply-system optimization." *J. Water Resour. Plng. and Mgmt.*, ASCE, 121(5), 392-398.

Taher, S. A., and Labadie, J. W. (1996). "Optimal design of water-distribution networks with GIS." *J. Water Resour. Plng. and Mgmt.*, ASCE, 122(4), 301-311.

Tu, M.-Y., Hsu, N.-S., and Yeh, W. W-G. (2002). "Optimization of reservoir management and operation with hedging rules." *J. Water Resour. Plng. and Mgmt.*, ASCE (in press).

Vairavamoorthy, K., and Lumbers, J. (1998). "Leakage reduction in water distribution systems: optimal valve control." *J. Hydraul. Eng.*, ASCE, 124(11), 1146-1154.

Varma, K. V. K., Narasimhan, S., and Bhallamudi, S. M. (1997). "Optimal design of water distribution systems using an NLP method." *J. Environ. Eng.*, ASCE, 123(4), 381-388.

Watkins, Jr, D. W., and McKinney, D. C. (1998). "Decomposition methods for water resources optimization models with fixed costs." *Adv. Water Res.*, 21, 283-295.

Williams, H. P. (1999). *Model Building in Mathematical Programming*, Fourth Edition, John Wiley & Sons Ltd, Chichester.

Wolsey, L. A. (1998). *Integer Programming*, Wiley Interscience, New York.

Wurbs, R. A. (1993). "Reservoir–system simulation and optimization models." *J. Water Resour. Plng. and Mgmt.*, ASCE, 119(4), 455-472.

Wurbs, R. A. (1996). *Modeling and Analysis of Reservoir System Operations*, Prentice Hall PTR, Upper Sadddle River, New Jersey.

Xu, C., and Goulter, I. C. (1999). "Reliability-based optimal design of water distribution networks." *J. Water Resour. Plng. and Mgmt.*, ASCE, 125(6), 352-362.

Yang, S., Hsu, N.-S., Louie, P. W. F., and Yeh, W. W-G. (1996a). "Water distribution network reliability: connectivity analysis." *J. Infrastruct. Sys.*, ASCE, 2(2), 54-64.

Yang, S., Hsu, N.-S., Louie, P. W. F., and Yeh, W. W-G. (1996b). "Water distribution network reliability: stochastic simulation." *J. Infrastruct. Sys.*, ASCE, 2(2), 65-72.

Yang, S., Sun, Y.-H., and Yeh, W. W-G. (2000). "Optimization of regional water distribution system with blending requirements." *J. Water Resour. Plng. and Mgmt.*, ASCE, 126(4), 229-235.

Yeh, W. W-G. (1985). "Reservoir management and operation models: A state-of-the-art review." *Water Resour. Res.*, 21(12), 1797-1818.

Yeh, W. W-G., and Yang, S. (1997). "A study on the efficiency of water resources allocation." *Proj. Completion Rep. to Water Resource Bureau*, Taipei, Taiwan, R.O.C.

Zheng, C., and Wang, P. (1996). "Parameter structure identification using tabu search and simulated annealing." *Adv. Water Res.*, 19(4), 215-224.